From Hesitancy Framings to Vaccine Hesitancy Profiles: A Journey of Stance, Ontological Commitments and Moral Foundations

Maxwell Weinzierl, 1 Sanda Harabagiu 1
1Human Language Technology Research Institute, The University of Texas at Dallas
{maxwell.weinzierl, sanda}@utdallas.edu

Abstract

While billions of COVID-19 vaccines have been administered, too many people remain hesitant. Twitter, with its substantial reach and daily exposure, is an excellent resource for examining how people frame their vaccine hesitancy and to uncover vaccine hesitancy profiles. In this paper we expose our processing journey from identifying Vaccine Hesitancy Framings in a collection of 9,133,471 original tweets discussing the COVID-19 vaccines, establishing their ontological commitments, annotating the Moral Foundations they imply to the automatic recognition of the stance of the tweet authors toward any of the CoVAXFRAMES that we have identified. When we found that 805,336 Twitter users had a stance towards some CoVAXFRAMES in either the 9,133,471 original tweets or their 17,346,664 retweets, we were able to derive nine different Vaccine Hesitancy Profiles of these users and to interpret these profiles based on the ontological commitments of the frames they evoked in their tweets and on value of their stance towards the evoked frames.

1 Introduction

Social media microblogging platforms, specifically Twitter, have become highly influential and relevant to shaping attitudes towards vaccination. With 206 million daily active users as of 2021, Twitter has substantial reach and daily exposure, being the most popular social network for news consumption (Auxier and Anderson[2021]). Since Twitter allows people to express their beliefs about vaccines and their hesitancy to vaccinate, their trust or mistrust in vaccines as well as their attitudes towards vaccination can help to prevent the spread of variants. 4. We don’t know the long-term effects of COVID-19 yet #GetTheShot

| Vaccine Hesitancy Framing 1: Governments hide vaccine safety information. |
|-----------------------------|--------------------------------------------------|
| STANCE: Accept              | Tweet: Why would the government block the Office for National Statistics from publishing side effects and deaths after taking covid vaccine? What are they hiding? |
| STANCE: Reject             | Tweet: @USER I am not talking about protection, but prima facie what i have heard from many in government and private hospital doctors is, 2 doses are very much effective in stopping mortality or high organ damage. Vaccine can’t stop covid, we are talking more about mortality reduction |

| Vaccine Hesitancy Framing 2: It is not known if the COVID-19 vaccines will provide protection against future variants. |
|-----------------------------|--------------------------------------------------|
| STANCE: Accept              | Tweet: It’s not a vaccine. The COVID-19 mRNA vaccine does not provide immunity to Covid or it’s variants so you can still catch Covid and transmit it to others making you asymptomatic. You will likely need a booster shot every 6 months, so get ready to roll up that sleeve every six mon |
| STANCE: Reject             | Tweet: Reasons to get the vaccine: 1. It can protect you in case your immune system can’t fight the virus. 2. It can help protect your community and vulnerable people. 3. It can help to prevent the spread of variants. 4. We don’t know the long-term effects of COVID-19 yet #GetTheShot |

Table 1: Examples of Vaccine Hesitancy Framings and tweets evoking them, while the tweet authors accept or reject the framing.

Vaccine Hesitancy Framings (VHFs), highlight issues regarding confidence in the safety of vaccines by using specific misinformation, as exemplified by the first VHF listed in Table 1 or erode the trust in vaccines by demotivating people from vaccination, as exemplified in the second VHF listed in Table 1. While VHFs are not directly expressed in tweets discussing vaccines, they can be inferred from the discourse spanning these tweets. Furthermore, tweet authors do not only evoke these VHFs, but they also express their stance towards them. Table 1 illustrates a tweet whose author agrees with the first VHF shown in the Table, thus adopting the framing and another tweet whose author disagrees with the

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Figure 1: Recognizing Vaccine Hesitancy Profiles (VHPs) by taking into account (1) the identification of Vaccine Hesitancy Framings (VHFs); (2) the stance of tweet authors towards the framings; and (3) the ontological commitments of the identified framings.

Vaccine hesitancy is a continuum between those that accept vaccines with no doubts, to those that absolutely refuse vaccines, with vaccine hesitant individuals in heterogeneous groups between these two extremes, according to (Larson et al. 2015). To uncover the Vaccine Hesitancy Profiles (VHPs), which was the main objective of our study, we focused on the Twitter discourse regarding the COVID-19 vaccines. Intuitively, all tweet authors sharing the same VHP are expected to also share some commonalities through the way they frame their hesitancy towards COVID-19 vaccines. Therefore, as illustrated in Figure 1, our methodology considered (A) the identification of VHFs from an index of 5,865,046 tweets discussing COVID-19 vaccines and (B) the recognition of the stance towards the VHFs evoked by 805,336 users. Furthermore, we relied on previous work in social psychology considered the Moral Foundations Theory (MFT) (Haidt and Graham 2007; Haidt and Joseph 2004) as a theoretical framework for analyzing moral framing, using the same five key values of human morality, emerging from evolutionary, social, and cultural origins. Each VHF was annotated with the Moral Foundation (MF) they imply. For example, for the first VHF illustrated in Table 1, the annotated MFs are: Harm, Betrayal and Authority while for the second VHF illustrated in the same table, the only annotated MFs is Betrayal. The annotated MFs informed the recognition of the tweet author stance towards the VHFs that are evoked in their tweets. These annotations have contributed to the automatic recognition of stance.

Figure 1 shows that our journey, from identifying VHFs (revealed as answers to questions about vaccine hesitancy), to finally recognizing the VHPs, involved also (C) the derivation of the ontological commitments of the VHFs, by categorizing them into misinformation, framings eroding trust in vaccines, framing building trust in vaccines, framings showcasing the health literacy of the tweet author or framings in which civil rights are brought up. This categorization enabled us to identify the common themes and concerns of the VHFs in each category, and to organize them into taxonomies, completing the ontological organization of the VHFs. These taxonomies, together with the stance information, allowed us to create a representation of each Twitter user that we recognized to have a stance towards the VHFs, and (D) to reveal the VHPs. The ontological information along with the stance information enable us to interpret the VHPs. For example, the tweet authors mostly evoking the first VHF illustrated in Table 1 belong to the profile of UNDECIDED, whereas the authors accepting the second VHF from the same table are DEMOTIVATED in their hesitancy, whereas those rejecting it belong to the profile of those that are MOTIVATED to vaccinate.

2 Identification of Vaccine Hesitancy Framings through Question/Answering

Current NLP methods (Luo, Zimet, and Shah 2019; Du et al. 2017) used for recognizing vaccine hesitancy assume that a neutral sentiment detected in a tweet is equivalent to hesitancy, while a positive sentiment is interpreted as acceptance of vaccination and a negative sentiment as refusal. However, as defined in (Larson et al. 2015), vaccine hesitancy refers to the delay in acceptance or refusal of vaccines despite availability of vaccination services. Moreover, vaccine hesitancy is informed by factors such as complacency, convenience, and confidence, which are framed in complex ways in language (Macdonald 2015). For example, when misinformation is used in framing vaccine confidence, it typically results in vaccine hesitancy. Similarly, when civil rights are highlighted in a particular framing, it promotes vaccine refusal, while when trust in vaccines is increased, it leads to vaccine acceptance, and eventual uptake. Therefore, developing novel NLP techniques capable of discovering framings of vaccine hesitancy in social media discourse is essential, especially for uncovering the various vaccine hesitancy profiles of users.

Recent work in NLP concerning automatic recognition of framings targeted the study of political bias and polariza-
Figure 2: A Question Answering Framework for (a) identifying Vaccine Hesitancy Framings as well as (b) tweets that potentially evoke a Vaccine Hesitancy Framing.

In a novel approach that uses Question Answering, illustrated in Figure 2, we have found that VHFs focusing on the COVID-19 vaccines can be successfully identified as answers to questions from the Vaccine Confidence Repository (VCR) (Rossen et al. 2019), which is a set of 18 questions targeting hesitancy, informed by the anti-vaccine content analysis reported in (Kata 2010). The same questions were used in the study reported in (Rossen et al. 2019) to discern hesitancy profiles from the answers returned on survey links available from Facebook pages and parenting forums. The questions from VCR targeted the Human Papillomavirus (HPV) vaccine. We adapted the questions by asking about the COVID-19 vaccine. These questions covered five different themes stipulating that: (T1) vaccines are unsafe and unnatural; (T2) vaccination is ineffective; (T3) redundant vaccinations; (T4) people should be free to decide if they want to vaccinate; and (T5) vaccination is a conspiracy. Instead of soliciting answers from Twitter users, we decided to (a) automatically find tweets that answer the same questions and (b) infer the framings evoked by the answers.

As shown in Figure 2, each question was processed, transforming it into a query that can be handled by a relevance model implementing the BM25 vector relevance model (Beaulieu et al. 1997). In addition, as in (Weinzierl and Harabagiu 2020), we considered the BERT-RERANK (Nogueira and Choi 2020) scoring function to re-rank the tweets provided by the BM25 relevance model. But, finding the answers to the questions required an index of tweets discussing the COVID-19 vaccines.

In order to obtain a collection of tweets discussing the COVID-19 vaccine, we started by obtaining approval from the Institutional Review Board at the University of Texas at Dallas. IRB-21-515 stipulated that our research met the criteria for exemption #8(iii) of the Chapter 45 of Federal Regulations Part 46.101(b). Afterwards, tweets discussing the COVID-19 vaccines were obtained by using the query "(covid OR coronavirus) vaccine lang:en". A collection of 9,133,471 original tweets and 17,346,664 retweets was obtained from the Twitter streaming API. These tweets were authored between December 18th, 2019, and July 21st, 2021. To detect duplications in the original tweets, we performed Locality Sensitive Hashing (LSH) (Das et al. 2007) with term trigrams, 100 permutations, and a Jaccard threshold of 50%, obtaining 5,865,046 unique original tweets discussing COVID-19 vaccines. We first build an index for 5,865,046 unique original tweets using Lucene (Foundation 1999), informing the relevance model.

Relevance judgements were produced on the 300 best ranked tweets from the first index, language experts categorizing afterwards the attitude against the predication of the question of each relevant tweet. Less than 60% of the tweets were judged relevant by two language experts from the University of Texas at Dallas. As shown in Figure 2, relevant tweets were categorized as accepting the predication, rejecting it and doubting it, with a Cohen Kappa score of 0.81, which indicates strong agreement between annotators (0.8-0.9) (McHugh 2012). From tweets sharing the same attitude towards the question predication, the Pyramid method (Nenkova and Passonneau 2004) was used to infer a query-focused multi-tweet summary, which was considered a VHF. In this way, we identified a set of 113 VHFs targeting the COVID-19 vaccine, which we assembled in CoVAXFRAMES. Then, each VHF from CoVAXFRAMES was reused as a question and processed by the relevance model against a new index containing all the 9,133,471 original tweets and 17,346,664 retweets. From the best-ranked 400,000 tweets retrieved for each VHF, only the tweets that had a relevance score above a threshold \( T_r = 2.0 \), selected from initial experiments, were considered to potentially evoke the VHF, which resulted in 19,233,144 tweets potentially evoking a
### THEME 1: Unsafe Vaccine
1.1: Vaccine unsafe because it is a bioweapon
1.2: The vaccine is unsafe poison
1.3: Bill Gates admits the vaccine is unsafe
1.4: The vaccine will make you gay
1.5: The vaccine makes you 5G compatible
1.6: The vaccine renders pregnancies risk

### THEME 2: Vaccine Ingredients
2.1: Vaccine injects a toxin in your bloodstream
2.2: The vaccine uses nanotechnology
2.3: The vaccine is gene therapy that activates a toxin in your body
2.4: The vaccine contains the virus

### THEME 3: Alternatives to the Vaccine
3.1: Homeopathic medicine as alternatives to vaccine
3.2: Vitamins as alternative to vaccine
3.3: Hydroxychloroquine as alternative to vaccine
3.4: Garlic as alternative to vaccine
3.5: Ivermectin as alternative to vaccine

### THEME 4: Vaccine Effect on Immune System
4.1: Overwhelms the immune system
4.2: Overrides the immune system
4.3: Immune system attacks children’s body

### THEME 5: Unnecessary Vaccine
5.1: Vaccine is a satanic plan to microchip population
5.2: A strong immune system is all you need
5.3: Chances of surviving infection are 99.99%
5.4: People with severe allergies should not be vaccinated

### THEME 6: Testing of the Vaccine
6.1: No long-term study of side effects
6.2: No vaccine efficacy or safety data
6.3: Vaccine has not been tested for at least 5 years

### THEME 7: Not Effective Vaccine
7.1: Vaccine doesn’t protect against COVID-19
7.2: Natural immunity lasts longer
7.3: Better protected by infection immunity

### THEME 8: Adverse Events of Vaccine
8.1: Vaccine interacts with people’s DNA
8.2: Vaccine replaces the genetic code with a synthetic one
8.3: More people die from adverse effects of vaccine than virus

### THEME 9: Information about Vaccines is Concealed
9.1: Pharmaceutical companies conceal information about breakthroughs or reintentions
9.2: The Federal government lied about vaccines to reduce the information about COVID-19 treatments
9.3: The Government conceals info about vaccine safety

### THEME 1: Trust in the Safety of Vaccines
1.1: COVID-19 vaccine is safe and efficient.
1.2: The Government has provided plenty of safety information about the COVID-19 vaccines.

### THEME 2: Motivation for Taking Vaccines
2.1: Unlikely that natural immunity is good idea.
2.2: Not worth having lingering effects of COVID-19.
2.3: Mitigating the effect of the infection.
2.4: Immunity more reliable than getting COVID-19.
2.5: Vaccine antibodies last longer and better.
2.6: Protect against the emerging variants.
2.7: Incentives increase the likelihood of taking the COVID-19 vaccine.
2.8: Children over 12 should be vaccinated to avoid distant learning.

### THEME 3: Trust in Effects of Vaccines
3.1: Vaccination against COVID-19 Strengthens the immune system.
3.2: More likely to get thrombosis from flying economy than from Astra Zeneca.
3.3: Johnson and Johnson COVID-19 vaccine allegedly preferred over Pfizer or Moderna for those with allergies.

### THEME 4: Trust in Role of Vaccines for Public Health
4.1: Getting vaccine will protect people who cannot get the jab.
4.2: The decision to not vaccinate puts all at risk.
4.3: Vaccines will lead to businesses opening.

### THEME 5: Trust in the Role of Pharmaceutical Companies in Fighting Infections
5.1: Vaccines are not profitable unless safe and effective.

### THEME 6: Lack of Trust in Ingredients of Vaccines
6.1: The mRNA vaccine uses the RNA of COVID-19 which leaves body soon after getting vaccinated.

### THEME 7: Trust in Testing of Vaccines
7.1: COVID-19 vaccination trials for children are vital.

### THEME 8: Adverse Events of Vaccine
8.1: Vaccine interacts with people’s DNA
8.2: Vaccine replaces the genetic code with a synthetic one
8.3: More people die from adverse effects of vaccine than virus

### THEME 9: Information about Vaccines is Concealed
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9.3: The Government conceals info about vaccine safety

### THEME 1: Lack of Trust in Safety of Vaccines
1.1: Why no accidental death policy?
1.2: Vaccine exemptions should be available.
1.3: No legal accountability for adverse events.
1.4: No long-term studies of safety or efficacy.

### THEME 4: Lack of Trust in Role of Vaccines for Public Health
4.1: People that do not believe that COVID-19 is real or do not believe that masks work should be exempt from the vaccination.
4.2: Because the authorities advocate so hard for COVID-19 vaccination should be the main reason for refusing the vaccine.
4.3: Preference for getting COVID-19 and fighting it off.

### THEME 5: Lack of Trust in the Role of Pharmaceutical Companies in Fighting Infections
5.1: Pharmaceutical companies will profit because COVID-19 waves will never end, thus requiring annual boosters.

### THEME 6: Lack of Trust in Ingredients of Vaccines
6.1: The COVID-19 Vaccine injects the dead SARS-COV2 virus in your body.

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**Figure 3:** Taxonomy of Themes and Concerns of (A) Misinformation, (B) Building Trust, (C) Eroding Trust, (D) Civil Rights, (E) Vaccine Literacy, and (F) Moral Foundations defined by the Moral Foundation Theory, annotated when implied in Vaccine Hesitancy Framings from CoVaxFRAMES.
3 Ontological Commitments of Vaccine Hesitancy Framings

The VHF’s were inspected first to distinguish which ones contain misinformation and which do not. Of the 113 VHFs from COVAXFRAMES, 38 VHFs were categorized as Misinformation framings. The remaining VHFs were categorized in the following way: 52 VHFs addressed issues of trust in vaccines, but without using misinformation; 32 VHFs addressed issues of CIVIL Rights. In addition, we inspected all VHFs to decide if they exhibit health literacy or lack of it: 28 VHFs were categorized as Literacy framings. For the VHFs addressing issues of trust in vaccines, we found that 27 VHFs are Eroding Trust in vaccines while 25 VHFs are Building Trust framings. This categorization allowed us to organize a Misinformation Taxonomy, which encodes the common themes and concerns of the Misinformation framings. Similarly, we have organized a taxonomy of Building Trust and a taxonomy of Eroding Trust. These taxonomies are illustrated in Figure 3. For the VHFs addressing Civil Rights issues, we have created only two themes, as we have done for the VHFs exhibiting Vaccine Literacy or lack thereof, in their respective ontologies.

In addition, all VHFs from COVAXFRAMES were annotated with as many Moral Foundations as they implied. Figure 3(F) lists the definitions of each MF from the Moral Foundation Theory (Haidt and Joseph 2004) that we have used. A computational linguist and an expert in public health have independently assigned MFs to all the VHFs, and the inter-judge agreement was a Cohen’s Kappa score of 0.85, where disagreements were resolved between annotators. The most common Moral Foundations were Harm and Subversion, occurring in 45 VHFs and 44 VHFs respectively out of the 113 VHFs, while the least common Moral Foundations were Cheating and Loyalty, occurring in 8 VHFs and 9 VHFs respectively. These ontological commitments that were organized in the COVAXFRAMES contributed to the discovery of hesitancy profiles, along with the information about the stance towards any of the VHFs evoked in tweets.

4 Stance Recognition

The recognition of the stance of a tweet author towards any of the COVAXFRAMES is made possible by the STANCEID-MORALITY system, illustrated in Figure 4. Given any VHF f from COVAXFRAMES and any tweet t that may evoke a VHF, produced by the Q/A framework illustrated in Figure 2, we hypothesize that if an Accept or Reject stance towards VHF f is recognized automatically, then the tweet t is recognized as evoking VHF f, otherwise tweet t does not evoke the VHF f. We also believed that the stance of the author of tweet t is revealed not only by the interactions between lexical, semantic and emotion information expressed in the tweet t, but also by their interactions with the Moral Foundations (MFs) implied by the VHF f. Therefore, we designed for the STANCEID-MORALITY system a novel neural architecture that combines the advantages of the contextual embeddings learned by COVID-Twitter-BERT-v2 (Müller, Salathé, and Kummervold 2020) with the Graph Attention Networks (GATs) (Velicković et al. 2018) where lexical, emotion, and semantic information can be processed (Weinzierl, Hopfer, and Harabagiu 2021) and a special case of Continuous Hopfield Networks (Ramsauer et al. 2020), namely Hopfield Pooling, where the MFs can be processed as well.

The processing of a VHF f from COVAXFRAMES and the tweet t that potentially evokes f starts in the STANCEID-MORALITY system with joint word-piece tokenization (Devlin et al. 2019), producing the sequence of word-piece tokens \([CLS] f_1 f_2 \ldots f_a obsess [SEP] [SEP] t_1 t_2 \ldots t_b [SEP] [SEP]\). This sequence of tokens is provided to COVID-Twitter-BERT-v2 for generating the corresponding contextualized embeddings.

![Figure 4: Neural architecture of STANCEID-MORALITY.](image-url)
Attention weights are computed using weights $\alpha_{i,j}$ where $W$ is a contextual embedding $g_{i-1} \in \mathbb{R}^{n \times n}$ as $h_i = W^T g_{i-1}$, where $W$ is a learned weight matrix. This hidden representation is required for computing the self-attention weights of each GAT:

$$\alpha_{i,j}^n = \frac{\exp(\text{LeakyReLU}((a^n)^T[h_i^n, h_j^n]))}{\sum_{k \in \text{adj}(i)} \exp(\text{LeakyReLU}((a^n)^T[h_k^n, h_i^n]))} \quad (1)$$

where $a^n$ is a learned weight vector of size $2F$, $[\ldots]$ represents concatenation; $\text{LeakyReLU}(x) = \max(0, 0.2x, x)$; and $\text{adj}(\ldots)$ produces the list of adjacent nodes for a given node from the Lexical, Emotion, or Semantic graphs. The attention weights $\alpha_{i,j}^n$ determine the output of each GAT at layer $n$:

$$g_i^n = \sigma\left( \sum_{j \in \text{adj}(i)} \alpha_{i,j}^n h_j^n \right) \quad (2)$$

where $\sigma$ is an exponential linear unit (ELU) nonlinearity (Clevert, Unterthiner, and Hochreiter, 2016).

Each of the $d$ layers of GATs has a hidden size $F$, producing a graph representation $G_{i}^d$, $G_{s}^d$, and $G_{f}^d$ respectively of size $L \times F$. The GAT hidden size $F$ and the number of layers $d$ are selected from experiments on the development collection, outlined in Section 3. These Lexical, Emotion, and Semantic Graph representations are concatenated together to form $G^d = \{G_i^d, G_s^d, G_f^d\}$, with $G^d \in \mathbb{R}^{L \times 3F}$, which is provided as input to all three Lexical, Emotion, and Semantic GATs for the next layer, producing $G^{d+1}$. This allows each Lexical, Emotion, and Semantic GAT to consider previous, Lexical, Emotion, and Semantic Graph representations jointly, learning graph node embeddings which consider interactions between different graphs. The output of the final GAT layers $G^d = \{G_i^d, G_s^d, G_f^d\}$ is provided to the Hopfield Pooling of Moral Foundation (HP-MF) module.

Each of the 10 MFs $m_i$ are each assigned a unique Moral Foundation Embedding (MFE) $m_{i0}^d \in \mathbb{R}^{3F}$, initialized randomly and learned throughout the training process of the STANCE-ID-MORALITY system. The MFEs of the $k$ MFs annotated for the VHF $f$, $m_i^0, m_i^1, m_i^2, ..., m_i^6$, are used as initial query embeddings for performing independent Hopfield Pooling (Weinzierl and Harabagiu, 2020a) on $G^d$. Hopfield pooling performs attention pooling $p$ times, where each iteration $j$ refines the query MFE $m_i^j$ from performing attention pooling on the outputs of the final GAT layers $G^d$ utilizing the previous MFE $m_i^{j-1}$ as the query. For each of the $k$ MFs judged within the VHF $f$, we perform attention pooling at each step $j$, from 1 to $p$, independently for each MF $m_i$. Attention weights are computed using $m_i^{j-1}$ as the query against the final lexical, emotion, and semantic word embedding $G^d = \{g_{i1}^d, g_{i2}^d, ..., g_{i6}^d\}$:

$$\beta_{x}^{i,j} = \frac{\exp(g_{x}^d \cdot m_{i}^{j-1})}{\sum_{y=1}^{L} \exp(g_{y}^d \cdot m_{i}^{j-1})} \quad (3)$$

Where $\cdot$ represents the dot product. These attention weights $\beta_{x}^{i,j}$, which range from 0 to 1, represent how closely the MFE $m_i^{j-1}$ aligns with each of the concatenated lexical, emotion, and semantic word embeddings $g_{x}^d \in G^d$. The updated MFE $m_i^j$ is then computed as a weighted sum, using $\beta_{x}^{i,j}$ as the weights, over the lexical, emotion, and semantic word embeddings $g_{x}^d \in G^d$:

$$m_i^j = \sum_{x=1}^{L} \beta_{x}^{i,j} g_{x}^d \quad (4)$$

Hopfield pooling is therefore performed for each of the $k$ initial MFEs $m_i^0, m_i^1, ..., m_i^6$ found in VHF $f$ by attention pooling $p$ times over $G^d$ to iteratively construct $m_i^1, m_i^2, ..., m_i^p$. These final $k$ MFEs are summarized into a single fixed-length representation by taking the average MFE as $z = \frac{1}{k} \sum_{i=1}^{k} m_i^p$. This embedding $z$ is provided to the stance recognition layer, which employs a fully connected layer with a softmax activation function to produce final probabilities $P(\text{Accept} \mid f, t), P(\text{Reject} \mid f, t)$, and $P(\text{No-Stance} \lor \neg \text{Evoke} \mid f, t)$, where we merge the probabilities $P(\text{No-Stance} \mid f, t)$ and $P(\text{Evoke} \mid f, t)$ into a single probability output, as a tweet with No Stance towards VHF $f$ and a tweet which does not evoke VHF $f$ are both ignored when we perform vaccine hesitancy profiling. The STANCE-ID-MORALITY system is trained end-to-end on the cross-entropy loss function:

$$\mathcal{L} = - \sum_{(s,f,t) \in D} \log P(s \mid f, t; \theta) \quad (5)$$

where $s \in \{\text{Accept}, \text{Reject}, \text{No-Stance} \lor \neg \text{Evoke}\}$, $D$ is a set of all training examples of labeled $[\text{tweet}, \text{VHF}]$ pairs, and $\theta$ is a set of all trainable parameters from STANCE-ID-MORALITY. These parameters are optimized with ADAM (Kingma and Ba, 2015), a variant of gradient descent, to minimize $\mathcal{L}$.

Table 2: Distribution of stance values for VHFs in the Training, Development, and Test splits of COVAXFRAMES.

| Split  | Evoke | Accept | Reject | No Stance | Total  |
|--------|-------|--------|--------|-----------|--------|
| train  | 8,390 | 5,241  | 1,668  | 1,481     | 10,250 |
| dev    | 941   | 567    | 211    | 163       | 1,115  |
| test   | 2,285 | 1,461  | 448    | 376       | 2,815  |
| Total  | 11,616| 7,269  | 2,327  | 2,020     | 14,180 |

Because the STANCE-ID-MORALITY system implements a supervised method for stance recognition, we relied on a training dataset, a development dataset as well as a testing dataset that allowed us to perform experiments and collect results. Generating these datasets was made possible by the annotations performed on the tweets deemed relevant for each
of the VHR questions used in the QA framework presented in Section 2. Researchers from the University of Texas at Dallas and public health experts from The University of California, Irvine judged (a) whether a tweet evokes any of the VHFs from CoVAXFRAMES; and (b) if so, they annotated the stance of the tweet’s author towards the VHF. 14,180 tweets were judged, with 11,616 tweets evoking one or more VHFs from CoVAXFRAMES. They were organized in [tweet, VHF] pairs, annotated with a stance value that could be Accept, Reject or No Stance. Statistics for the number of tweets evoking a VHF, as well as of the stance their authors have towards the VHF, are provided in Table 2. To evaluate the quality of judgements, we randomly selected a subset of 1,000 tweets (along with the VHF against which they have been judged a stance value), which have been judged by at least two different language experts. Inter-judge agreement was computed using Cohen’s Kappa score, yielding a score of 0.67 for the stance of tweets for COVID-19 VHFs, which indicates moderate agreement between annotators (0.60–0.79).

When we performed stance recognition with the STANCEID-MORALITY system on all the tweets that may evoke a VHF from CoVAXFRAMES, produced by the QA system responding to any CoVAXFRAMES (discussed in Section 2), we identified a total of 1,741,269 tweets from 805,336 users which held an Accept or Reject stance towards one or more VHF from CoVAXFRAMES.

5 Deriving Vaccine Hesitancy Profiles

Revealing the VHPs from the 805,336 users having a stance towards any of the CoVAXFRAMES requires first to produce a representation of each of these users that encodes knowledge about the way the users frame their vaccine hesitancy as well as the stance they have regarding it. To encode the knowledge regarding vaccine hesitancy, we relied on the ontological commitments we have produced for CoVAXFRAMES. More specifically, we decided to use the themes encoded in the taxonomies illustrated in Figure 3 and considered the stance each user had towards VHFs within each theme. As shown in Figure 5, we produced for each user a vector \( u \in \mathbb{R}^{|H|} \), where \( H = 27 \) is the total number of themes across all taxonomies illustrated in Figure 4 (i.e. 9 themes from the Misinformation taxonomy; 7 themes from the taxonomy of Building Trust; 7 themes from the taxonomy of Eroding Trust; and 2 themes each for Civil Rights and Vaccine Literacy). The values of the vector \( u \) were computed by:

\[
    u_h = \sum_{(t,f,s) \in U(u,h)} \frac{SV(s)}{|U(u,h)|}
\]

where \( U(u,h) \) is the set of tweets \( t \) authored by \( u \), evoking a VHFs \( f \) belonging to the theme \( h \); while \( s \) represents the stance value of \( u \) towards \( f \), with \( s \in \{\text{Accept, Reject}\} \). \( SV(s) = 1 \) if the user \( u \) accepted \( f \) and \( SV(s) = -1 \) if \( u \) rejected \( f \).

In this way, we obtained 805,336 sparse vectors representing the users, that enabled us to cast the recognition of VHPs as a clustering task, which could reveal the groups of users that manifest vaccine hesitancy with similar stance towards VHFs that share the same knowledge, encoded at the level of the hesitancy theme. For this purpose, we performed sparse k-means \((\text{Lloyd} 1982)\) clustering on these user vector representations, varying the number of clusters \( k \) from 2 to 12. The final number of profiles, \( k \) was selected following the Elbow method \((\text{Thorndike} 1953)\), i.e. by (a) computing the L2-distance of these distances for each VHP. We found that the number of VHPs for \( k = 9 \) as satisfying the Elbow method, as it obtained the minimum average distance from each user vector to the centroids of the VHPs, with an L2-distance of 1.05.

Interpretation of the Vaccine Hesitancy Profiles

The 9 VHPs were manually inspected by exploring the tweets of the 50 users closest to the VHP centroid vectors, and each VHP was assigned a name based on the interpretation. Figure 6 supports our interpretations by illustrating how the predominant stances of profile users are interacting with (A) the ontology commitments; and (B) the MFs.

The UNDECIDED VHP includes 177, 836 users (22%) who are on the fence about the COVID-19 vaccines. These users are characterized by a 50/50 split in acceptance and rejection of the misinformation that the VHF that the COVID-19 vaccine is an unsafe poison, while also having a 60/40 split in trust in the government to provide accurate COVID-19 vaccine safety information. They tend to pick-and-choose which VHFs they Accept and Reject, leading to theme-level inconsistencies in their beliefs. Users from this VHP tend to both adopt and reject VHFs with MFs of Subversion, Harm, Authority, and Care. They are the primary target of those that propagate COVID-19 vaccine misinformation, such as the MISMATCHERS, and adopt misinformation nearly as often as they reject it.

The DEMOTIVATED VHP includes 89, 827 users (11%) who have largely lost their motivation to vaccinate against COVID-19. These users overwhelmingly accept demotivating VHFs, e.g. that the COVID-19 vaccine does not provide immunity, that you can still get infected even after getting
vaccinated, and that breakthrough cases after getting fully vaccinated are common. The users in this profile accept some COVID-19 vaccine misinformation about the vaccine ingredients, but primarily they are complacent, considering that the perceived risks of the COVID-19 vaccine do not justify the uptake. The predominant MFs of the VHF they evoke are: Authority and Subversion with an undertone of Harm, Betrayal, and Care. Both pairs of Authority and Subversion, and Care and Harm, are diametrically opposed MFs, which may explain why they believe that vaccination is necessary for others, but not themselves.

The Mandate Debaters VHP includes 86,306 users (11%) who discuss the civil rights issues surrounding mandating vaccination against COVID-19. These users heavily adopt the VHFs that that everyone should make their own informed decisions about COVID-19 vaccines and that people should not be chastised on whether they decide to avoid the vaccine, but otherwise debate whether vaccine mandates are ever appropriate. They overwhelmingly adopt the VHF that all healthcare workers should be vaccinated against COVID-19, and that refusing the COVID-19 vaccine puts the lives of others at risk, but also adopt erosion of trust framings which surround perceived issues with COVID-19 vaccines, such as their concern that the AstraZeneca vaccine may cause blood clots. The predominant the MFs the VHF they evoke are Harm and Subversion, with an additional focus on Fairness and Authority. They have the highest adoption of Fairness of all the VHPs, which aligns with their focus on what is fair with regard to COVID-19 vaccine mandates.

The Misinformers VHP includes 37,906 users (5%) who aggressively propagate COVID-19 vaccine misinformation. These users intensely adopt VHF's containing misinformation or eroding trust in vaccines, and completely reject VHF's about vaccine mandates. They are entirely demotivated to take the COVID-19 vaccine because they believe that it is unnecessary, since the survival rate of COVID-19 is 99.99%, and that the vaccine does not provide immunity. They also believe that the COVID-19 vaccine is an unsafe poison, that the vaccine is experimental and should not be used for children, and that the vaccine has not been sufficiently tested. These users evoke VHF's with MFs that clearly align with those evoked by the UNDECIDED, and entirely adopted by the DE-
MOTIVATED. Espousing these MFs corresponds to the undue influence of the MISINFORMERS, leading to the propagation of COVID-19 vaccine misinformation to a wider audience, which we can see is often adopted by both the UNDECIDED and the DEMOTIVATED.

The CONSPIRATORS VHP includes 26,822 users (3%) who believe in COVID-19 vaccine conspiracy theories. These users solely adopt VHFs referring to conspiracy theories, e.g. the vaccine contains a neurotoxin; or the mRNA vaccine is gene therapy which will change your DNA; or the government hides vaccine safety information, and that the vaccine itself contains the virus. The VHF they adopt have MFs such as Degradation, Harm, Subversion, and Authority, and they belong to the only VHP which has heavy focus on Degradation.

The CONCERNED VHP includes 67,845 users (8%) who follow closely the science regarding the COVID-19 vaccines, maintaining high vaccine literacy, but still have some minor concerns with the COVID-19 vaccines, manifested in their adoption of VHFs that erode trust in vaccines. These users adopt VHF which focus on the ability to reduce mortality by the COVID-19 vaccine, believing that the vaccines protect against grave forms of COVID-19 and are absolutely necessary for those at-risk. They believe that the COVID-19 vaccines will protect against emerging variants, but are generally concerned with some specific VHFs, such as that the AstraZeneca vaccine may cause blood clots, the belief that the vaccines do not provide immunity, or the concern that the vaccine may not have been tested for long enough time yet. They adopt VHF with MFs such as Authority, Care, and Loyalty.

The PROMOTERS VHP includes 135,933 users (17%) who actively promote the role of the COVID-19 vaccines for public health. These users are characterized by overwhelming adoption and propagation of VHFs that build trust in vaccines, and the framings they evoke highlight their vaccine literacy. These users overwhelmingly accept that vaccination is key in protecting yourself and others against COVID-19, that vaccination protects against severe COVID-19, that the vaccines will protect against emerging variants, and that the government has provided plenty of vaccine safety information. They also have a secondary focus on mythbusting through rejecting misinformation and trust-eroding framings, such as rejecting that the COVID-19 vaccine has not been sufficiently tested. These users also adopt many VHFs that build trust in vaccines, while the VHF they evoke have the MFs of Care, Authority, and Loyalty.

The MOTIVATORS VHP includes 131,717 users (16%) who specifically try to motivate users to get vaccinated. These users are similar to the PROMOTERS, widely adopting of VHF for building trust in vaccines, e.g. the COVID-19 vaccines protect against the emerging variants, or the vaccines trigger your body to naturally create immunity more reliably than getting COVID-19, and that the COVID-19 vaccines have been tested, tracked, and are safe. They also reject misinformation and VHF eroding trust in vaccines. These users have high vaccine literacy, and the VHF they evoke have the MFs of Care and Authority.

The MOTIVATED VHP includes 51,144 users (6%) who share stories of themselves and others getting vaccinated against COVID-19, including reassurance that the side effects are very minor and that the vaccines are extremely safe. They adopt trust-building framings such as that the lingering effects and risks of COVID-19 are much worse than the minor side effects of getting vaccinated. The VHF they evoke have the MFs of Care and Authority.

### 6 Experimental Results

To evaluate the VHPs, we performed an external evaluation by sampling pairs of users and judging if these users should belong in the same or a different cluster based on the content of their tweets. We selected the 50 users for each VHP having user vector representations that are closest to the VHP’s centroid vector. For each of the 9 VHPs, we then sampled from these 50 users without replacement 20 pairs of users from the same VHP and 20 pairs of users from different VHPs, obtaining a total of 360 pairs of users. This approach ensured that bias was removed from the manual evaluation, such that each pair of users had a 50% chance of being from the same VHP and a 50% chance of being from a different VHP. Language experts were tasked with judging if each pair was from the same VHP cluster or from a different VHP cluster by inspecting the content of the tweets of each pair of users. We then compared these judgements to the VHP assignments obtained by k-means clustering. K-means clustering of k = 9 produced a Rand index of 0.840 and a Fowlkes-Mallows index of 0.847 [Fowlkes and Mallows1983], with Precision of 0.815 and Recall of 0.880. The random-clustering baseline had 0.5 for the Rand index, the Fowlkes-Mallows index, Precision, and Recall. The comparison with the random-clustering baseline demonstrates quantitatively that the 9 VHP clusters are better-than-random. Moreover, our results show that the 9 VHPs are of high quality, since users were 7.3 times more likely to be identified as similar if they were from the same VHP and 4.0 times more likely to be identified as different if they were from different VHPs.

The discovery of the VHPs was made possible by the recognition of the tweets that evoke the VHF that we identified and the stance of the tweet authors. Therefore, we also evaluated the quality of stance recognition. Stance recognition performance towards VHFs in the test collection of CoVAXFRAMES was evaluated on three systems: (1) the STANCEID-BASELINE system; (2) the STANCEID system; and (3) the STANCEID-MORALITY system. The STANCEID-BASELINE system utilizes the “[CLS]” embedding from COVID-Twitter-BERT-v2 as the framing stance recognition input embedding $z$. The STANCEID system utilizes Lexical, Emotion, and Semantic Graph Attention Networks to produce the framing stance recognition input embedding $z$ [Weinzierl, Hopfer, and Harabagiu2021]. The STANCEID-MORALITY system, described in Section 4 and illustrated in Figure 4, utilizes Lexical, Emotion, and Semantic Graph Attention Networks along with Hopfield Pooling of Moral Foundations to perform framing stance recognition. Hyper-parameters were selected based on initial experiments on the training and development collections of CoVAXFRAMES. All system hyperparameters follow those of
and Harabagiu (2021), while STANCEID-MORALITY also performs Hopfield Pooling with Moral Foundations with $p = 6$, has a GAT hidden size $F = 32$, and $d = 3$ stacked GAT layers. All systems follow the same training schedule: 10 epochs, a linearly decayed learning rate of $5e-4$ with a warm-up for 10% of training steps, and an attention drop-out rate of 10%. Results are provided in Table 3.

Performance was determined based on Precision (P), Recall (R), and F1 score for detecting the Accept and Reject values of stance. We also compute a Macro averaged Precision, Recall, and F1 score. The STANCEID-BASELINE system produced a Macro F1 score of 69.1, which demonstrates the advantage of pre-training BERT on domain-specific COVID-19 tweets and fine-tuning stance recognition systems. The STANCEID system produced a Macro F1 score of 72.4, which indicates that integrating Lexical, Emotional, and Semantic Graphs improves stance recognition. The STANCEID-MORALITY system produced a Macro F1 score of 75.2, supporting our hypothesis that MFs play a key role in detecting tweets which evoke VHFs along with recognizing acceptance and rejection of VHFs. The results also show that detecting rejection of VHFs is more difficult than detecting acceptance.

Improvements in stance recognition for the STANCEID system are driven by results for the Reject stance. The Reject stance has the fewest number of [tweet, VHF] pairs, with only 2,327 instances in a dataset of 14,180 [tweet, VHF] pairs. The STANCEID system overcomes this resource constraint by integrating additional Lexical, Emotion, and Semantic information. Stance recognition is further improved by the STANCEID-MORALITY system for both the Accept and Reject stance values. The STANCEID-MORALITY system clearly benefits from integrating MF resources with the Hopfield pooling approach, which provides the best results on recognizing both acceptance and rejection.

### 7 Ethics Statement

Accurate vaccine hesitancy profiling at scale has the potential to enable public health researchers to design customized interventions to target users most likely to be convinced to vaccinate. Public health outreach could become much more personalized, directly addressing the themes, concerns, and moral priorities held by users on Twitter. Potential downsides to the approach outlined in this paper include the mistaken assignment of Twitter users to hesitancy profiles, due to sarcasm, jokes, or untruthful postings, which may be difficult for our system to recognize. Additionally, many users may change their stance and remove or rebut their own tweets over time. The downside of mistaken user hesitancy profiling is minimal, as we expect our system to be used by public health practitioners when developing their interventions. Questionnaires that precede the application of an intervention would filter out Twitter for incorrect hesitancy profiles.

Our data collection process was reviewed and approved by the Institutional Review Board at the University of Texas at Dallas. All tweets collected were public, and only the tweet IDs and annotations will be shared, such that others must go through the approval process to use the data. We expect COVAXFRAMES would become a valuable resource for identifying Vaccine Hesitancy Framings, and recognizing the stance each Twitter user has towards those framings. While we believe that the annotation quality of COVAXFRAMES is high (0.67 Cohen’s Kappa score), mistakes in judgements of stance are likely due to difficult complex phenomena, such as sarcasm. We believe that such potential misjudgments are rare and thus minimally impact the quality of the hesitancy profiles.

### 8 Conclusion

In this paper we described a novel methodology for recognizing Vaccine Hesitancy Profiles (VHFs), applied to the COVID-19 vaccines. This methodology relies on the identification of how people frame their vaccine hesitancy, what Moral Foundations are implied by their Vaccine Hesitancy Framings (VHFs), and what stance the Tweet authors have towards COVAXFRAMES. By considering the ontological commitments of the VHFs from COVAXFRAMES we derived nine VHFs of 805,336 Twitter users having a stance towards some COVAXFRAMES. The interpretation of the VHFS revealed that 22% of these users are UNDECIDED; 11% are DEMOTIVATED; 11% are MANDATE DEBATERS; 5% are MISINFORMERS; 3% are CONSPIRATORS; 8% are CONCERNED; 17% are PROMOTERS; 16% are MOTIVATORS; and 6% are MOTIVATED.

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### Table 3: Framing Stance Recognition results on the COVAXFRAMES test collection.

| System             | Macro F1 | Macro P | Macro R | Accept F1 | Accept P | Accept R | Reject F1 | Reject P | Reject R |
|--------------------|----------|---------|---------|-----------|----------|----------|-----------|----------|----------|
| STANCEID-BASELINE  | 69.1     | 68.8    | 69.5    | 81.0      | 79.3     | 82.8     | 57.2      | 58.2     | 56.2     |
| STANCEID           | 72.4     | 69.6    | 75.4    | 80.6      | 77.1     | 84.5     | 64.1      | 62.1     | 66.3     |
| STANCEID-MORALITY  | 75.2     | 73.0    | 77.9    | 83.6      | 77.8     | 90.5     | 66.8      | 68.3     | 65.4     |
