

Understanding COVID-19 Vaccine Campaign on Facebook using Minimal Supervision

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Abstract—In the age of social media, where billions of internet users share information and opinions, the negative impact of pandemics is not limited to the physical world. It provokes a surge of incomplete, biased, and incorrect information, also known as an infodemic. This global infodemic jeopardizes measures to control the pandemic by creating panic, vaccine hesitancy, and fragmented social response. Platforms like Facebook allow advertisers to adapt their messaging to target different demographics and help alleviate or exacerbate the infodemic problem depending on their content. In this paper, we propose a minimally supervised multi-task learning framework for understanding messaging on Facebook related to the COVID vaccine by identifying ad themes and moral foundations. Furthermore, we perform a more nuanced thematic analysis of messaging tactics of vaccine campaigns on social media so that policymakers can make better decisions on pandemic control.

Index Terms—COVID-19 vaccine, social media, facebook ads, minimal supervision, weak labeling.

I. INTRODUCTION

Since January 2020, worldwide public health has been threatened by the novel coronavirus – the outbreak was declared a global pandemic by the World Health Organization (WHO) [1]. COVID-19 is the first pandemic in the history in which technology and social media are being used on a massive scale to keep people safe, informed, productive, and connected. Yet, at the same time, the growing proliferation of social media can be used for spreading hoaxes and false information leading to what is commonly referred to as an infodemic [2]. Social

A school COVID-19 vaccine mandate imposed by the government is an overreach of power and takes away the right of parents to make medical decisions for their children.

Fig. 1: Example of an ad highlighting analysis dimensions (1) theme, (2) moral foundation.

media discourse help increase polarization around topics related to COVID-19 vaccines, such as the vaccine mandate, natural immunity, vaccine efficacy, religious sentiment, and vaccine equity. Moral Foundation Theory (MFT) [4], [5] suggests a theoretical framework for analyzing the morality, containing six basic moral foundations (Table. I). Past work has shown that the theory can help explain ideological differences and

CARE/HARM: Saying that someone other than the speaker deserves care or gets harmed. Reflects the base of Maslow's Hierarchy of Needs [3]. Security, Shelter, Food, Water, Warmth.
FAIRNESS/CHEATING: Justice, rights, and autonomy, comparison to other groups. Equality of Opportunities. Social Intolerance to "Free-Rider".
LOYALTY/BETRAYAL: Patriotism and self-sacrifice for the group (Or failure to provide it, in the case of betrayal). It is active anytime people feel that it's "one for all, and all for one."
AUTHORITY/SUBVERSION: Deference (or opposition) to legitimate authority and respect for traditions. Social order and the obligations of hierarchical relationships, such as obedience, respect, and the fulfillment of role-based duties.
SANCTITY/DEGRADATION: Not simply a religious value. Respect for the human spirit. Social aversion of personal degradation. Degradation causes disgust. Physical and spiritual contagion, including virtues of chastity, wholesomeness, and control of desires. It underlies the widespread idea that the body is a temple which can be desecrated by immoral activities and contaminants (an idea not unique to religious traditions).
LIBERTY/OPPRESSION: Feelings of people towards those who dominate them and restrict their liberty. The hatred of bullies and dominators motivates people to come together, in solidarity, to oppose or take down the oppressor.
NONE: Does not fall under any other foundation.

TABLE I: Six basic moral foundations.*

social group membership [6]–[12]. Often there is a significant correlation between the vaccine debate and its moral foundation (MF).

However, sponsored contents have been used to reach more people on social media to disseminate their agendas. For example, Fig. 1 presents a sponsored ad on Facebook representing 'vaccine mandate' as the ad theme and *overreach of power and takes away the right*, falling under the 'liberty/oppression' moral foundation. Therefore, detecting moral foundation and theme from text are vital components in understanding advertisers' intention, key talking points, policies.

Our goal in this paper is to take a first step toward analyzing the landscape of vaccination campaigns on social media. We focus our experiments on a timely topic, COVID-19 vaccination campaign. Our main contributions are twofold: (1) to identify the ad theme & moral foundation; (2) to build on this characterization to analyze the messaging across different demographics, geographic, and timelines. We analyze over 28K COVID vaccine related ads on Facebook, associating ads with 6 moral foundations and including 'none', it's a 7-class classification problem. We also identify the theme of the ads, a 15-class classification problem.

Our theme analysis is motivated by previous studies [13]–[15] that created code-book of COVID-19 vaccine arguments. Besides, our moral foundation analysis is inspired by social science studies [16]–[18] that demonstrated relation between

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Moral Foundations	Example of messages
Care/Harm	Protect yourself and others. Help those most vulnerable. Public health can assist you. Stay healthy and safe.
Fairness/Cheating	Everyone has an interest in beating this outbreak. Infection does not discriminate. We have an interest in everyone getting appropriate care. Vaccine should be free for everyone.
Loyalty/Betrayal	Do your part, take the shot for your family, friends, country. We need to protect our community. I'm loyal to you and want to keep you safe.
Authority/Subversion	Limited resources should go first to healthcare workers and those caring for us. Scientific evidence and common sense show that protective measures really work. Listen to your local public health official. Respect healthcare workers and the risks they are taking. Trust science.
Sanctity/Degradation	Be a good role model for others. Be willing to sacrifice your wants for community needs. Help nurture the spirits of those needing comfort. Look for ways to serve others.
Liberty/Oppression	COVID can threaten our safety and freedom. We want our community to be free from fear of contagion. The quicker we beat this, the quicker we recover and return to normal.

TABLE II: Example messages corresponding to each moral foundation provided to annotators.

moral foundation and COVID related health decisions.

In this paper, we suggest a minimally supervised multi-task learning approach to understand COVID-19 vaccine campaign in Facebook. The purpose of minimal supervision is to compensate for the lack of annotated data by exploiting the maximum potential of the available data. For MF, we generate weak labels from dedicated lexicons developed for identifying moral foundation. For theme, we use a pre-trained textual inference model to identify paraphrases in a large collection of COVID-19 vaccination ads from Facebook and assign theme based on cluster assignment (Details in IV-A). We focus on the following research questions (RQ) to analyze vaccine campaigns on social media:

- **RQ1.** What are the narratives of the messaging? (section V-C)
- **RQ2.** How does entity type fulfill messaging roles? (section V-D)
- **RQ3.** Which demographics and geographic are reached by the advertisers and their messages? (section V-E)
- **RQ4.** Do ads follow current COVID status? (section V-F)

We summarize the main contributions of this paper as the following:

- 1) We formulate a novel problem of using minimal supervision to analyze the landscape of vaccine campaigns on Facebook. Our dataset is publicly available here[†].
- 2) We suggest a minimally supervised multi-task learning framework with three different learning strategies to identify ad theme and moral foundation.
- 3) We investigate the COVID vaccine ads on Facebook from four angles: narratives (thematic and moral foundation analysis), entity types (who is funding the ad), reach (who saw the ads), and whether the ads reflect current COVID situations.

II. RELATED WORK

Recent studies have shown narrative analysis and opinion mining of COVID-19 pandemic discourse in social media

[†]https://github.com/tunazislam/Covid_FB_AD_MinimalSup

Themes	Definition
EncourageVaccination	Promoting vaccination to control pandemic.
VaccineMandate	Arguments about vaccine mandate, vaccine passport/card.
VaccineEquity	Acknowledging no nation, state, or individual's life is more important or more deserving than another's.
VaccineEfficacy	Arguments saying that the vaccine is safe, lessens the symptoms.
GovDistrust	Arguments saying people do not have trust on Governmental institutions or authority figures.
GovTrust	Arguments saying people have trust on Governmental institutions or authority figures.
VaccineRollout	Information about vaccination sites and availability of appointments.
VaccineSymptom	Symptoms associated with the vaccine, e.g., fever, sore arm etc.
VaccineStatus	Information regarding rate of vaccination, hospitalization, death etc.
VaccineReligion	Arguments about religion and vaccine.
VaccineDevelopment	Broadcasting information about the vaccine development and approval.
CovidPlan	Good policies to deal with COVID-19.
VaccineMisinformation	Conspiracy theories, fake news related to vaccine.
NaturalImmunity	Natural methods of protection against COVID.
Vote	Encourage residents to vote by iterating messages related to COVID vaccine.

TABLE III: Theme definition provided to the annotators.

and news media [19]–[25]. Also, there are recent studies on online perceptions about COVID-19 vaccination related to public health measures [26]–[28] and moral foundations [29]–[33]. Nowadays, targeted online advertising is one of the main communication channels, allowing hyper-local sponsors to campaign during the pandemic. Sponsored content on social media can be shared with various narratives, including information and misinformation, to disseminate agendas targeting specific demographics and geographic. Mejova and Kalimeri [34] analyzed a smaller set of COVID-19 related Facebook ads messaging by identifying advertisers and their targets. Silva and Benevenuto [35] monitored COVID related Facebook Ads in Brazil to identify misinformation. Our work takes a different approach to analyze COVID vaccine related Facebook ads by identifying themes and moral foundation that motivate sponsors. Our work falls under the broad scope of weak supervision [36]–[39] and multi-task learning [40]–[44].

III. DATASET DETAILS

We collected approximately 28,000 COVID vaccine related ads focusing on United States from December 2020 - January 2022 using Facebook Ad Library API[‡] with the search term ‘COVID-19 vaccine’, ‘COVID vaccine’, ‘vaccination’, ‘vaccine’, ‘coronavirus vaccine’, ‘corona vaccine’. Our collected ads were written in English. For each ad, the API provides ad ID, title, ad body, funding entity, spend, impressions, distribution over impressions broken down by gender (male, female, unknown), age (7 groups), location down to states in the USA. We have duplicate content among those collected ads because the same ad has been targeted to different regions and demographics with unique ad id. We have 9,920 ads with different contents.

A. Data Annotation

We manually annotated 557 ads for themes and moral foundation. To ensure quality work, we provided annotators with 23 examples covering all six moral foundations (Table. II) and theme definition of 15 themes (Table III). Two annotators from the Computer Science department manually annotated a subset of ads (20%) to calculate inter-annotator agreement

[‡]<https://www.facebook.com/ads/library/api>

using Cohen’s Kappa coefficient [45]. This subset has inter-annotator agreements of 73.80% for MF and 65.60% for theme which are substantial agreements. In case of a disagreement, we resolved it by discussion. Rest 80% of the data was annotated by one of the graduate students between the two. We had one female and one male annotator, and the age range was 30 – 40.

IV. METHODOLOGY

In this section, we start by describing the labeling technique that produces numerous but imprecise (weak) labels. Then, we put forward two learning strategies to better exploit the available labels. Finally, we show the main components of multi-task learning model. An overview of the model is illustrated in Fig. 2.

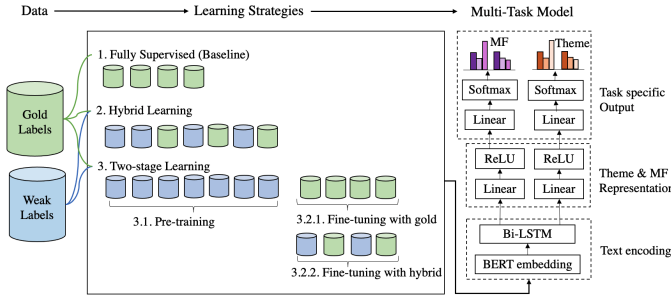


Fig. 2: An overview of our proposed framework. Best viewed in electronic format (zoomed in).

A. Weak Label Generation

In this section, we describe how to generate weak labels from ad content that can be incorporated as weak sources in our model.

1) *Themes*: First, we go through relevant research conducted by the health informatics, computational social science, public health, psychology communities and ground our analysis through constructing a list of potential themes for COVID related ads [15], [46]–[49]. Then, we consult with two researchers in Computational Social Science and finalize the relevant themes with corresponding phrases. The full list of phrases for each theme can be observed in Table IV. To generate the weak labels for themes, we ground the phrases (from corresponding theme) in a set of 28k unlabelled COVID-19 vaccine related ads and match similarity between their Sentence BERT embeddings [50]. We measure the cluster purity using silhouette score [51]. We use threshold based on closest distance to limit assignments. Bar plot with the number of assigned ads to each cluster with and without threshold and 2D visualizations of clusters are shown using t-SNE [52] in Fig. 3. We use $threshold \leq 0.5$ resulting 21,851 ads.

2) *Moral Foundation*: Weak label for moral foundation is generated by analyzing text based on the MFT relying on the use of a lexical resource, the Moral Foundations Dictionary (MFD) [6]. Similar to Linguistic Inquiry and Word Count (LIWC) [53], [54], MFD associates a list of related words with each one of the moral foundations. We analyze ad’s text by counting the number of occurrences of words in the text

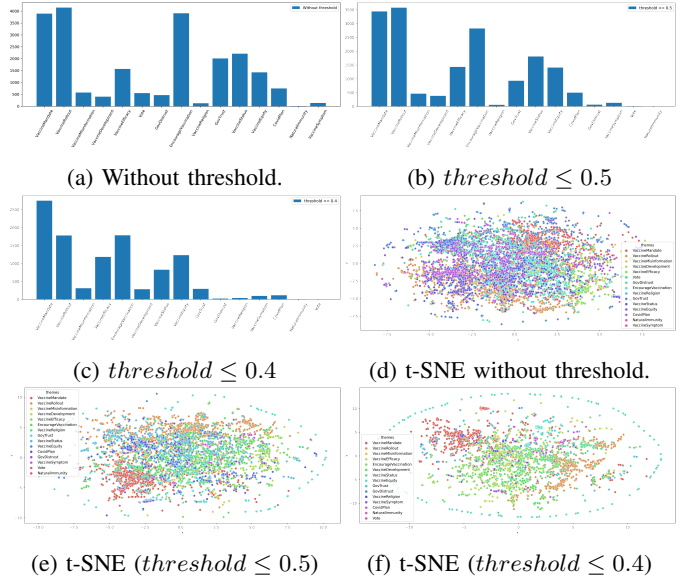


Fig. 3: Bar plot and 2D visualization of cluster assignment for themes without and with threshold. Best viewed in electronic format (zoomed in).

which also match the words in the MFD. In this process, same ad might get multiple moral foundations based on lexicon matching. To assign one MF for each ad, we pick the MF having the highest number of keyword matching with our text. Given that MFD does not have lexicon for liberty/oppression moral foundation, we use the same lexicon curated by Pacheco et al. [15]. We annotate an ad as liberty/oppression MF if it contains at least two keywords.

3) *Quality of Weak Label*: To assess the weak label quality, we compare the weak labels with the ground truth labels (557 ads). The accuracy and macro-avg F1 score of the weak label for theme are 0.513 and 0.337 respectively. For moral foundation, the accuracy and macro-avg F1 score are 0.417 and 0.248 correspondingly. We observe that the accuracy and macro-avg F1 score of the weak label are significantly better than random (0.067) for theme and comparatively better than random for moral foundation (0.143), indicating that our noisy labeling approach has acceptable quality.

B. Learning Strategies

We devise two learning strategies so that model can have access to larger datasets, which may benefit its generalization capabilities at both tasks.

1) *Hybrid Learning*: To avoid the risk of highly biased model, instead of using fully weakly supervised batches to train the multi-task model, we create mixed batches with part gold, part noisy labels.

2) *Two-stage Learning*: We separate the learning process into two stages, i.e., (1) pre-training stage using a large but noisy dataset, (2) fine-tuning stage using gold labels. We use a transfer learning technique by freezing the hidden layers except for the task-specific layers of our model. Therefore, we

Themes	Phrases
EncourageVaccination	"Get your vaccine", "Get the shot", "Get jabbed", "Protect our community by getting vaccinated", "We can all do our part", "Your shot matters", "I encourage everyone to get their shot when they can", "Getting vaccinated is the best way to protect yourself and everyone around you", "Take your best shot", "Be the part of the solution", "Win lottery by getting vaccinated", "Sleeve up", "Vaccines save lives", "Collect your vaccine incentives", "Take the vaccine for your family, for your friends, for your country", "Get vaccinated", "Get free vaccine and free lunch", "Get boosted", "Vax up", "Call us and we will answer your questions regarding COVID vaccine", "Do your part to stop pandemic", "This is our best shot", "Join a discussion about vaccine"
VaccineMandate	"Forcing people to take experimental vaccines is oppression", "The vaccine has nothing to do with COVID-19, it's about the vaccine passport and tyranny", "The vaccine mandate is unconstitutional", "I'm not against the vaccine but I am against the mandate", "I have freedom to choose not to take the vaccine", "I choose not to take the vaccine", "I am free to refuse the vaccine", "It is not about COVID, it is about control", "My body my choice", "Medical segregation based on vaccine mandates is discrimination", "The vaccine mandate violates my rights", "I support vaccine mandate", "Firing over vaccine mandates is oppression", "Vaccine passports are medical tyranny", "I won't let the government tell me what I should do with my body", "I won't have the government tell me what to do", "The vaccine mandate is not oppression because vaccines lower hospitalizations and death rates", "The vaccine mandate is not oppression because it will help to end this pandemic", "The vaccine mandate will help us end the pandemic", "If you don't get the vaccine based on your freedom of choice, don't come crawling to the emergency room when you get COVID", "If you refuse a free FDA-approved vaccine for non-medical reasons, then the government shouldn't continue to give you free COVID tests", "You are free not to take the vaccine, businesses are also free to deny you entry", "We need a vaccine mandate to end this pandemic", "You are free not to take the vaccine, businesses are free to protect their customers and employees", "Support vaccine passport", "If you choose not to take the vaccine, you have to deal with the consequences", "We don't support vaccine passport", "If it is your body your choice, then insurance companies should stop paying for your hospitalization costs for COVID", "Check vaccine card for events", "Airlines require vaccine passport", "Proof of vaccine is required", "Vaccine passport is useful for reopen", "Workers have declined COVID-19 Vaccine", "Falsely labeling the injection as a vaccine is illegal"
VaccineEquity	"Vaccine should be available for everyone", "Vaccine should be free of cost", "Everyone has right to get free COVID vaccine", "We don't have equal access to vaccine", "We should ensure vaccine access to vulnerable communities"
VaccineEfficacy	"The vaccine works", "The vaccine is safe", "Vaccines do work, ask a doctor or consult with an expert", "The COVID vaccine helps to stop the spread", "Unvaccinated people are dying at a rapid rate from COVID-19", "There is a lot of research supporting that vaccines work", "The research on the COVID vaccine has been going on for a long time", "Millions have been vaccinated with only mild side effects", "Millions have been safely vaccinated against COVID", "The benefits of the vaccine outweigh its risks", "Vaccine is safe for pregnant woman", "The vaccine has benefits", "The vaccine is safe for women and kids", "The vaccine won't make you sick", "The vaccine isn't dangerous", "The vaccine won't kill you", "The COVID vaccine isn't a death jab", "The COVID vaccine doesn't harm women and kids", "COVID-19 vaccine ingredients are safe"
GovDistrust	"We have lack of trust in the government", "The government is a total failure", "Never trust the government", "Biden is a failure", "Biden lied people die", "The government and Fauci have been dishonest", "The government always lies", "The government has a strong record of screwing things up", "The government is good at screwing things up", "The government is screwing things up", "The government is lying", "The government only cares about money", "The government doesn't work logically", "Do not trust the government", "The government doesn't care about people's health", "The government won't tell you the truth about the vaccine", "Biden will not hold China accountable"
GovTrust	"We trust the government", "Biden is tackling COVID", "The government cares for people", "We are thankful to the government for the vaccine availability", "Hats off to the government for tackling the pandemic", "It is a good thing to be skeptical of the government, but they are right about the COVID vaccine", "It is a good thing to be skeptical of the government, but they haven't lied about the COVID vaccine", "Biden is helping to end the pandemic", "The government can be corrupt, but they are telling the truth about the COVID vaccine", "Trump initiated COVID vaccine", "The government can be corrupt, but they are not lying about the COVID vaccine", "Biden will hold China accountable"
VaccineRollout	"Vaccine appointment is available", "Schedule your vaccine appointment", "No appointment needed", "Walk-in vaccine clinic is available", "Drive through vaccine site is available", "Mobile clinic is available here", "Vaccine clinic has been set up", "New vaccine center has been opened", "CDC recommends vaccine for kids", "FDA authorized COVID vaccine for children ages 5 to 11 years old"
VaccineSymptom	"I got fever after taking the vaccine", "Know the vaccine symptom", "COVID vaccines can cause blood clots", "The vaccine has side effects", "The vaccine is dangerous for people with medical conditions", "I won't take the vaccine due to medical reasons"
VaccineStatus	"Half of the population are fully vaccinated", "Here is the vaccine statistics", "Update of vaccine status", "COVID-19 update", "COVID death is real", "Sign up for vaccine update", "We need volunteers for vaccine site", "Vaccination rate is slow", "Vaccination rate is high", "Infection rate is lower", "COVID vaccine information is here", "The pandemic is not a lie, hospitalizations are on the rise"
VaccineReligion	"The vaccine is against religion", "The vaccines are the mark of the beast", "The vaccine is a tool of Satan", "The vaccine is haram", "The vaccine is not halal", "I will protect my body from a man made vaccine", "I put it all in God's hands", "God will decide our fate", "Allah will protect us", "The vaccine contains bovine, which conflicts with my religion", "The vaccine contains aborted fetal tissue which is against my religion", "The vaccine contains pork, muslims can't take the vaccine", "Jesus will protect me", "The vaccine doesn't protect you from getting or spreading COVID, God does", "The COVID vaccine is another religion", "The vaccine is not against religion, get the vaccine", "No religion ask members to refuse the vaccine", "Religious exemptions are bogus", "When turning in your religious exemption forms for the vaccine, remember ignorance is not a religion", "Disregard for others' lives isn't part of your religion", "Jesus is trying to protect us from COVID by divinely inspiring scientists to create vaccines"
VaccineDevelopment	"COVID vaccine research has been going on for a while", "Plenty of research has been done on the COVID vaccine", "The technologies used to develop the COVID-19 vaccines have been in development for years to prepare for outbreaks of infectious viruses", "The testing processes for the vaccines were thorough didn't skip any steps", "The vaccine received FDA approval", "Vaccine uses mRNA technology", "the vaccine is not properly tested, it has been developed too quickly", "COVID-19 vaccines have not been through the same rigorous testing as other vaccines", "The COVID vaccine is experimental", "The COVID vaccine was rushed through trials", "The approval of the experimental vaccine was rushed"
CovidPlan	"Expand vaccine distribution", "We are working on vaccine distribution", "COVID rescue plan", "Cash relief", "More COVID testing center", "Setting up vaccine clinic", "Support small business", "Reopen country", "Reopen school", "Rebuilding economy", "COVID stimulus check", "Unemployment benefit", "Expand mask and PPE supply"
VaccineMisinformation	"Animal shelters are empty because Dr Fauci allowed experimenting of various COVID vaccines/drugs on dogs and other domestic pets", "Fauci tortures dogs and puppies", "The COVID vaccine is a ploy to microchip people", "Don't trust vaccine conspiracy", "Bill Gates wants to use vaccines to implant microchips in people", "Globalists support a covert mass chip implantation through the COVID vaccine", "There is aborted fetal tissue in the COVID Vaccines", "COVID vaccines contain aborted fetal cells", "The COVID vaccine will make you sterile", "COVID vaccine will affect your fertility", "The vaccine will not make you sterile", "The COVID vaccine will not affect your fertility", "No difference if fertility rate has been found between vaccinated and unvaccinated people", "Vaccines were tested on fetal tissues, but do not contain fetal cells", "Vaccines do not contain aborted fetal cells", "Vaccine misinformation is floating around", "Don't believe in vaccine misinformation"
NaturalImmunity	"Natural methods of protection against the disease are better than vaccines", "Herd immunity is broad, protective, and durable", "Natural immunity has higher level of protection than the vaccine", "Embrace population immunity", "I trust my immune system", "I have antibodies I do not need the vaccine", "Natural immunity is effective", "Natural immunity would require a lot of people getting sick", "Experts recommend the vaccine over natural immunity", "The vaccine has better long term protection than to natural immunity", "Natural immunity is not effective", "Experts aren't sure how long hybrid immunity lasts", "Natural immunity is highly variable"
Vote	"Please vote", "Your vote matters", "Go vote", "Vote today"

TABLE IV: Themes and phrases to show how sponsors use social media to influence the narrative on public health crisis. Best viewed in electronic format (zoomed in).

learn the model’s parameters on the weakly labeled dataset. Then, we fine-tune with fully supervised batches, i.e., gold label batches (mentioned as *Two-stage learning1*), as well as with a hybrid version, i.e., involving both noisy and gold labels in the batch (named as *Two-stage learning2*).

C. Multi-task Learning Framework

Our proposed minimally supervised multi-task learning model consists of three main components: the text encoder, the decoder to decode the output of the encoder, and task specific output by summing cross-entropy losses for both tasks.

1) *Text Encoder*: We adopt a bidirectional long short-term memory network (Bi-LSTM) [55], [56] as our text encoder. To encode the input sentence, we first embed each word in a sentence to a low-dimensional vector space [57]. The input to the text encoder component is a fixed-length word sequence from an ad $w = \{w_1, w_2, \dots, w_n\}$, where n is the sequence length. We use pre-trained BERT [58] to encode the text sequence into a sequence of embeddings, $e^w = \{e_1^w, e_2^w, \dots, e_n^w\}$, where $e^w \in \mathbb{R}^{n \times d_e}$ and d_e is the dimension of the word embedding. Bi-LSTM is employed to attain contextualized representations of words, $H = \{h_i | h_i \in \mathbb{R}^{2d_h \times d_e}\}$ by following operation:

$$h_i = [\overrightarrow{LSTM}(e_w) \oplus \overleftarrow{LSTM}(e_w)] \quad (1)$$

where d_h denotes the dimension of hidden state from an unidirectional LSTM, while $\overrightarrow{LSTM}(\cdot)$ and $\overleftarrow{LSTM}(\cdot)$ stand for forward and backward LSTM, respectively and \oplus represents concatenation.

2) *Decoder*: We then extract theme and MF-specific features from the encoded hidden states, by applying linear layers and nonlinear functions, i.e., ReLU [59]. The computation process is formulated as below:

$$r_i^t = ReLU(W_r^t h_i + b_r^t) \quad (2)$$

$$r_i^m = ReLU(W_r^m h_i + b_r^m) \quad (3)$$

where $r_i^t \in \mathbb{R}^{d_r}$ and $r_i^m \in \mathbb{R}^{d_r}$ are theme and moral foundation representations, d_r is the dimension of the representation. $W_r^t, W_r^m \in \mathbb{R}^{d_r \times 2d_h}$ and $b_r^t, b_r^m \in \mathbb{R}^{d_r}$ are learnable weights and biases.

3) *Task Specific Output*: Finally, we receive two series of task specific distributions by following:

$$P_i^t = softmax(W_o^t r_i^t + b_o^t) \quad (4)$$

$$P_i^m = softmax(W_o^m r_i^m + b_o^m) \quad (5)$$

where $W_o^t, W_o^m \in \mathbb{R}^{d_i \times d_r}$ and $b_o^t, b_o^m \in \mathbb{R}^{d_i}$ are trainable parameters and d_i denotes the task specific output label dimension. We use dropout [60] between individual neural network layers. Shuffled mini-batches with Adam [61] optimizer is used. We use cross-entropy loss as the objective function as following:

$$\mathcal{L}_t = -\frac{1}{n} \sum_i \hat{P}_i^t \log(P_i^t) \quad (6)$$

$$\mathcal{L}_m = -\frac{1}{n} \sum_i \hat{P}_i^m \log(P_i^m) \quad (7)$$

Model	MF		Theme	
	Accuracy	Macro-avg F1	Accuracy	Macro-avg F1
Fully supervised	0.688	0.204	0.250	0.050
Hybrid learning	0.752	0.510	0.690	0.579
Two-stage learning1	0.631	0.202	0.338	0.135
Two-stage learning2	0.697	0.242	0.259	0.260

TABLE V: Model performance for MF and theme prediction.

where \hat{P}_i^t and \hat{P}_i^m represent ground truth theme and moral foundation distribution for the text. Overall learning objective is conducted by joint training of the multi-task learning framework with the following objective:

$$\min_{\theta} \mathcal{L} = \mathcal{L}_t + \mathcal{L}_m + \gamma \|\theta\|_2 \quad (8)$$

where θ stands for trainable parameters, $\|\theta\|_2$ is L_2 regularization of θ and γ is a controlling term.

V. EXPERIMENTS

A. Experimental Setup

We evaluate a total of three settings (Fig. 2): (1) full supervision, which trains under a fully supervised low-resources setting where we only have a small fraction of gold label data (557 ads) for both tasks. We randomly split the data to three subsets, namely training set (60%), validation set (20%), and test set (20%); (2) hybrid learning experiment, at first we extract 30% gold label data for mixing with weakly labeled data and keep the rest of the gold data for testing. After the mixture of gold and noisy labeled data, we randomly split it into 80% training and 20% validation set for hybrid learning strategy; and (3) two-stage learning by pre-training a base model using weak labels and then refining using both gold and hybrid labels. For pre-training, we randomly split weakly labeled data into training (80%) and validation (20%) set. In fine-tuning step for *two-stage learning1*, we randomly split gold labeled data train-validation-test (60 – 20 – 20). For *two-stage learning2*, we randomly select 30% of weakly labeled data and mix them with gold trained data. Then, retrain our pre-trained model by freezing the hidden layers and tweaking the task specific layers.

Hyperparameter Setup: In the text encoder, we set the text sequence length, $n = 100$, and the word embedding dimension d_e , hidden states d_h , theme and MF representations d_r are set to 768, 256, 128, dropout rate = 0.2, batch size = 32, learning rate = 0.001, number of epochs = 100. Our early stopping criterion is the lowest validation loss and we stop the learning if the loss does not decrease for 10 consecutive epochs.

B. Results

We repeat each experiment 3 times and report the average performance (with p -value < 0.05 by paired t-test [62]) in Table V. We notice that our fully supervised baseline model struggles to predict ad themes. On the other hand, model achieves the best performance in hybrid learning strategies where training batches include both noisy and gold labels. We obtain accuracy of 75.2% and macro-average F1 score of

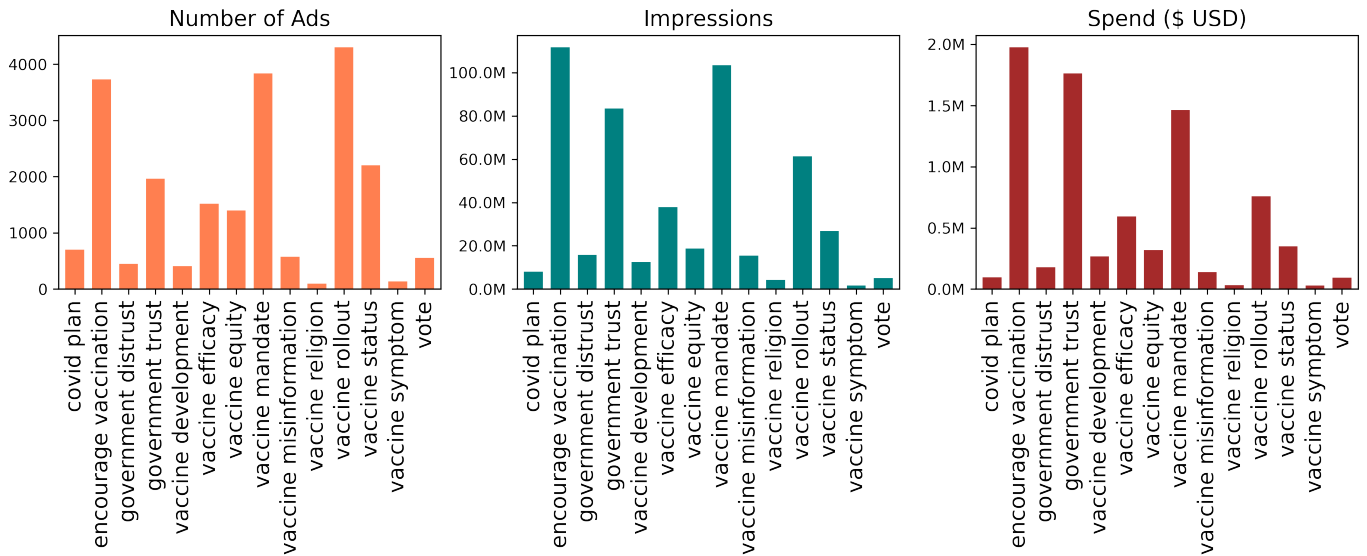


Fig. 4: Distribution of ad themes by number of ads, impressions, and spend.

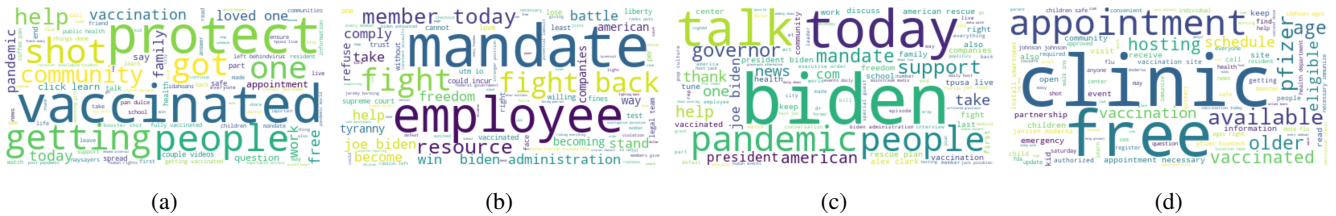


Fig. 5: Wordcloud for four messaging themes based on the popularity of ad impressions, expenditure, and number of sponsored ads. (a) encourage vaccination, (b) vaccine mandate, (c) government trust, (d) vaccine rollout.

51.0% for moral foundation prediction task. In theme prediction task, we achieve 69.0% accuracy and 57.9% macro-average F1 score. Though both of the two-stage learning strategies obtain comparable performance in MF prediction, we see lower accuracy on theme prediction. Because of the highly imbalanced data, we notice sharp drop of macro-avg F1 score. In conclusion, comparing this strategy to the fully supervised approach (baseline), the hybrid learning strategy seems to be a strong proposal to identify ad theme and moral foundation while using a multi-task learning approach.

C. Narrative Analysis

To answer **RQ1**, we analyze the messaging strategies used by the advertisers (Fig. 4). By impressions and spend, the most popular messaging theme is ‘encourage vaccination’, accounting for approximately 24% of total spend and 22% of total impressions. Narratives belonging to this category promote vaccination *to protect their loved one, family, friends, and community as well as end the pandemic* using ‘loyalty/betrayal’ moral foundation. Based on impression, the next most popular messaging category is ‘vaccine mandate’, which features narratives focusing *Biden’s vaccine mandate respective to freedom and tyranny*. Based on spend, the second most popular messaging theme is ‘government trust’, which focuses

on narratives supporting *Government’s vaccination policy*, emphasizing ‘care/harm’ moral foundation. On the other hand, sponsored ads mostly have a ‘vaccine rollout’ messaging theme (19.7%) focusing on *appointment availability of the free vaccine, vaccine eligibility information from FDA and CDC based on age, and information regarding drive-through/walk-in/mobile vaccine clinic*. To show the noticeable qualitative differences, we create wordcloud with the most frequent words from those selected four messaging themes. Fig. 5 shows the visual representation of the text for each of 4 theme category. Words are usually single words, and the importance of each tag is shown with font size and color.

D. Distribution of Messaging by Entity Type

At first, we select top 5 funding entities based on their expenditure. Next, we categorize funding entities into four types (based on Facebook page category), i.e., Public health, Commercial, Nonprofit, and Political. Then, we select top 5 funding entities based of their expenditure for each category. Table VI shows the list of our selected entities. Fig. 6 shows that the high spend on ‘government trust’ narratives comes mostly from commercial and political entities. Public health entities spend more on ‘vaccine rollout’, ‘encourage vaccination’, and ‘vaccine efficacy’ narratives. similarly, non-

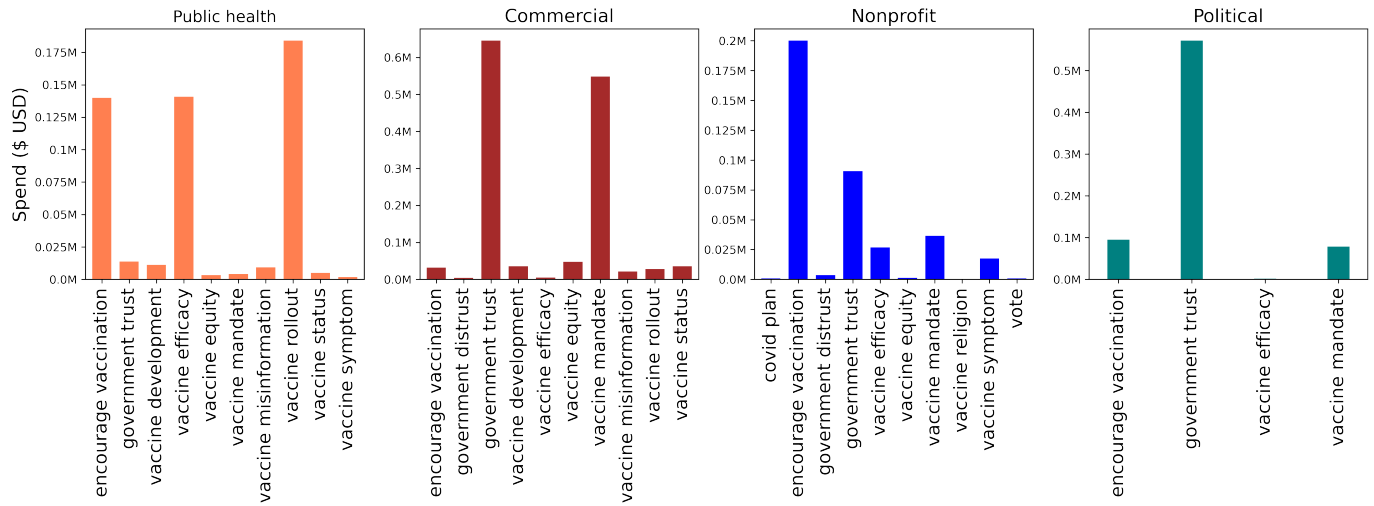


Fig. 6: Distribution of ad themes by funding entity type.

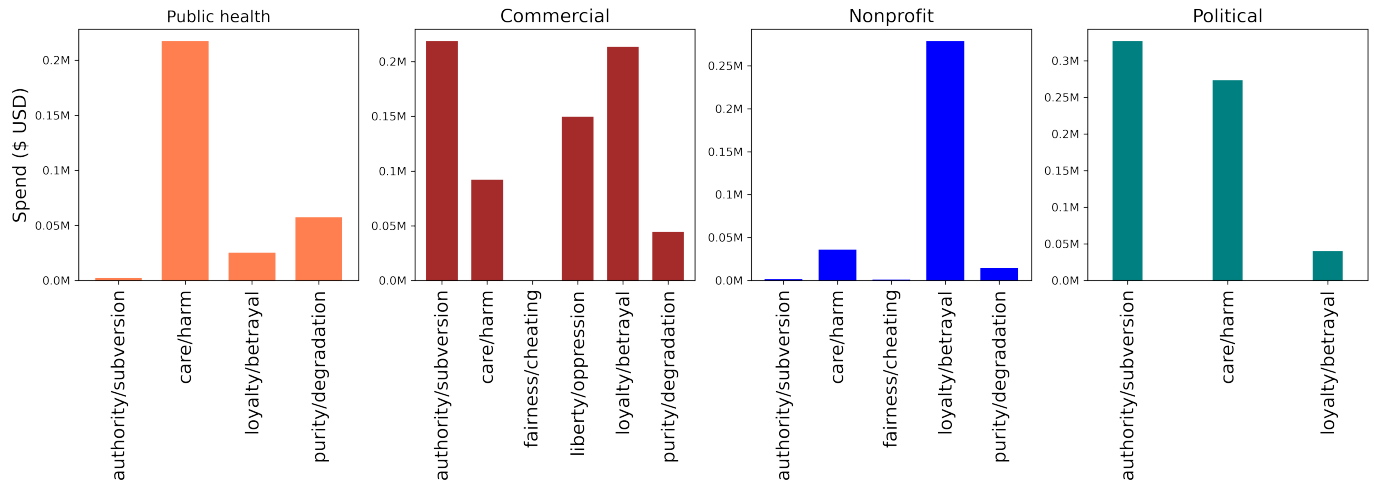


Fig. 7: Distribution of ad's moral foundation by funding entity type.

Type	Entity
Public health	Children's Health System of Texas
Public health	New York City Department of Health and Mental Hygiene
Public health	South Carolina Department of Health & Environmental Control
Public health	South Dakota Department of Health
Public health	Washington State Department of Health
Commercial	Pfizer Inc.
Commercial	ATTN: INC.
Commercial	Daily Wire
Commercial	BMO Harris Bank
Commercial	NEWSMAX MEDIA, INC.
Political	JB for Governor
Political	Kemp for Governor Inc
Political	Save America Joint Fundraising Committee
Political	Future Majority, Inc
Political	Terry for Virginia
Nonprofit	Turning Point USA, Inc.
Nonprofit	American Health Care Association and National Center for Assisted Living
Nonprofit	PICO California Action Fund
Nonprofit	Ad Council
Nonprofit	PROJECT HOPE

TABLE VI: List of entities.

Liberal	Conservative
Friends for Kathy Hochul	North Carolina Republican Party
House Majority Forward	TEXANS FOR SENATOR JOHN CORNYN INC.
INDIVISIBLE ACTION	JIM JORDAN FOR CONGRESS
Alexandria Ocasio-Cortez for Congress	Friends of Matt Gaetz
Charlie Crist for Governor	RAND PAUL FOR US SENATE
Election Fund of Steven Fulop 2021	UNSILENCED MAJORITY
JAY CHEN FOR CONGRESS	Schmitt for Senate
Elicker 2021	Dr Scott Jensen for Governor

TABLE VII: List of funding entities based on political view.

profit agency focus on 'encourage vaccination' theme (Fig. 6). Fig. 7 shows the distribution of moral foundation by entity type based on expenditure. Public health entities focus

more on 'care/harm', where as nonprofit entities focus on 'loyalty/betrayal'. Both political and commercial advertisers focus on 'authority/subversion' moral foundation (Fig. 7). To compute the statistical significance, we perform chi-square test [63] by taking theme distribution over moral foundation to build contingency tables separately for public health, commercial, nonprofit, and political categories. We choose the value of significance level, $\alpha = 0.05$, and our test results show that the p-value < 0.05 for all 4 categories. Therefore, we reject the null hypothesis, indicating some association between theme

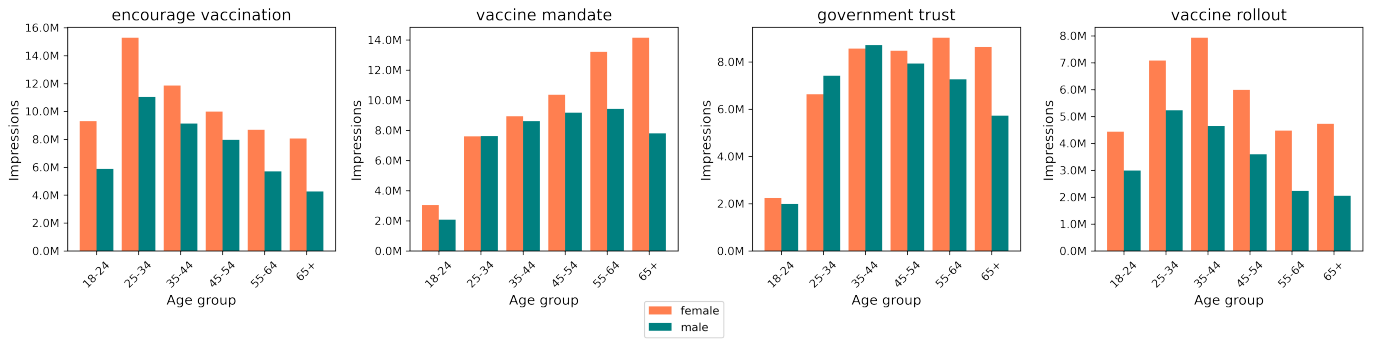


Fig. 8: Demographic distribution over impressions for selected four themes. T-test hypothesis testing results are in Table VIII.

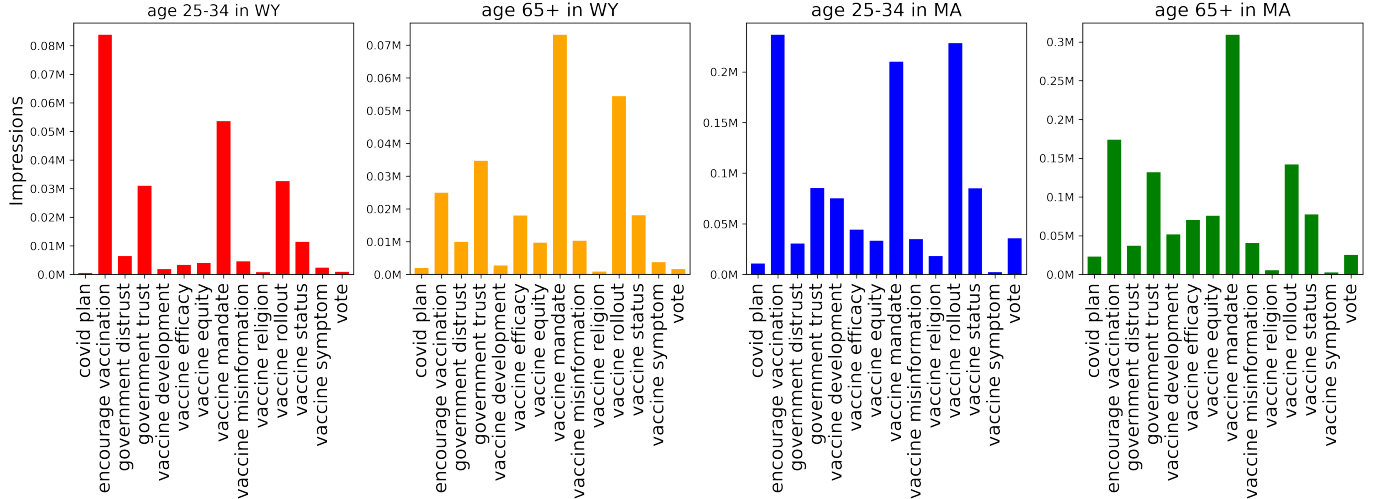


Fig. 9: Distribution of ad themes by demographics and geographic. T-test hypothesis testing results are in Table VIII.

Null Hypothesis, H_0	Alternate Hypothesis, H_a	T-test statistics	P-value
More females than the males from age range 25-34 do not view 'encourage vaccination' ads.	More females than the males from age range 25-34 view 'encourage vaccination' ads.	9.85**	0.0002
More females than males from older age (65+) do not watch 'vaccine mandate' ads.	More females than males from older age (65+) watch 'vaccine mandate' ads.	2.09 ^{ns}	0.09
More females than males from older age (55+) do not watch 'government trust' ads.	More females than males from older age (55+) watch 'government trust' ads.	1.37 ^{ns}	0.229
More females than the males from age range 35-44 do not view 'vaccine rollout' ads.	More females than the males from age range 35-44 view 'vaccine rollout' ads.	8.87**	0.0003
Population from age range (25 - 34) do not view 'encourage vaccination' ads in WY.	Population from age range (25 - 34) view 'encourage vaccination' ads in WY.	9.62**	0.0002
Older population (65+) do not view narratives from 'vaccine mandate' ads in WY.	Older population (65+) view narratives from 'vaccine mandate' ads in WY.	0.596 ^{ns}	0.577
Population from age range (25 - 34) do not view 'encourage vaccination' ads in MA.	Population from age range (25 - 34) view 'encourage vaccination' ads in MA.	4.02*	0.010
Older population (65+) do not view narratives from 'vaccine mandate' ads in MA.	Older population (65+) view narratives from 'vaccine mandate' ads in MA.	2.94*	0.032

** = highly statistically significant at p-value < 0.01; * = statistically significant at p-value < 0.05; ns = statistically not significant (p-value > 0.05).

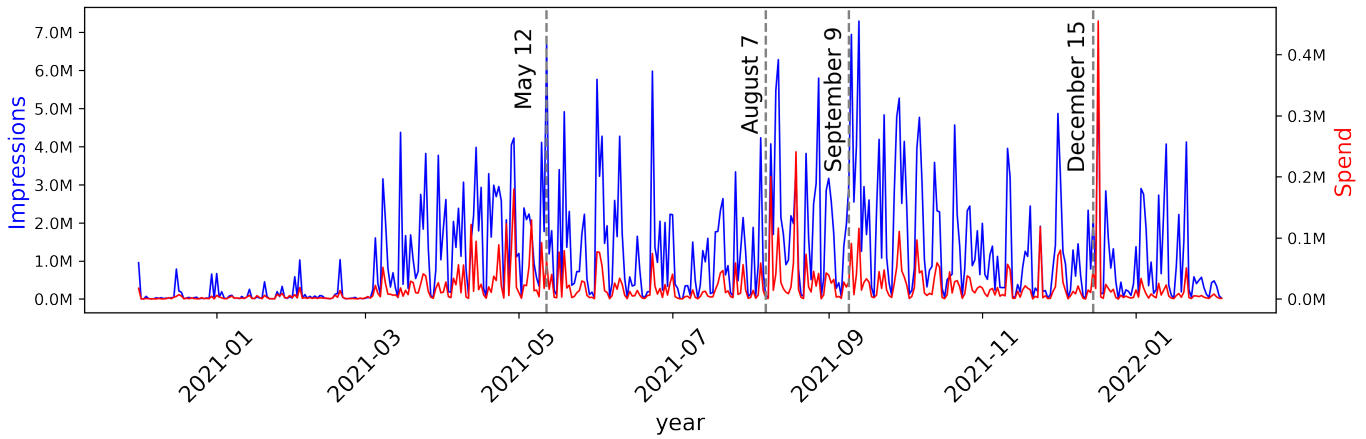
TABLE VIII: T-test of the influence of audiences' demographics and geographics on ad impressions.

and moral foundation.

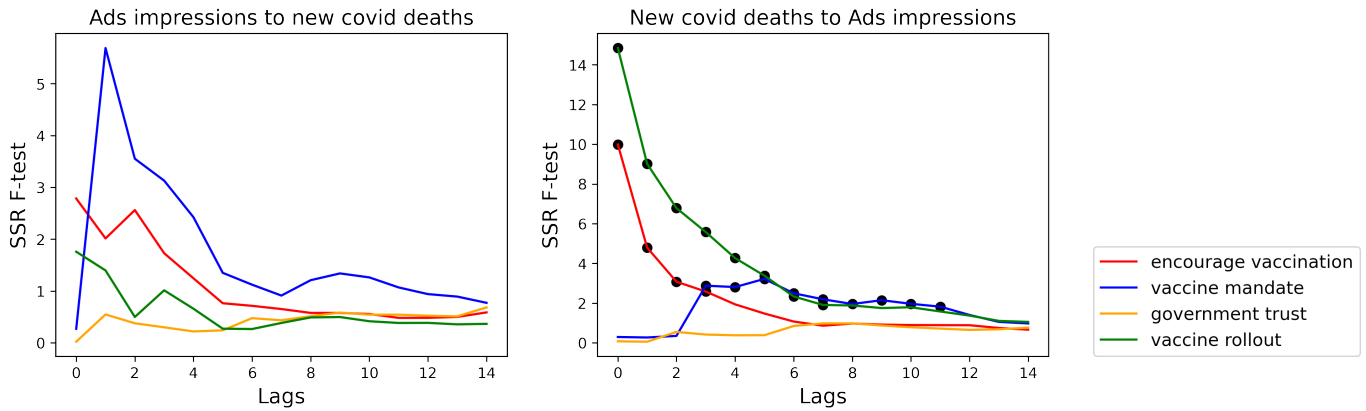
Looking further into the political group, we notice that this pattern primarily reflects the spending of *J.B. for Governor*. This funding entity sponsored political campaign for Jay Robert (J.B.) Pritzker, who is currently serving as the 43rd governor of Illinois. The narratives mainly focused on the 'authority/subversion' moral foundation by stating *how under Pritzker's leadership, Illinois administers most COVID-19 vaccine doses of any U.S. state*. Among the public health category, *South Carolina Department of Health & Environmental Control* has the highest expenditure on the 'vaccine rollout' theme, which has 'care/harm' moral foundation. Commercial agency *Daily Wire* spends more on vaccine related ads. The *Ad Council* pays the most among the nonprofit group to encourage people

to get vaccinated, emphasizing on 'loyalty/betrayal' moral foundation.

Distribution of Messaging by Advertisers' Political View: To understand existing knowledge of MFT [6], [7], we extend our analysis towards political advertisers' views, i.e., *conservative* and *liberal*. We select 16 funding entities (Table VII) and look for their views at OpenSecrets.org. We find that liberals mostly focus on 'encourage vaccination' theme and 'care/harm' moral foundation whereas conservatives mainly focus on 'vaccine mandate' theme and 'authority/subversion' moral foundation. We again perform chi-square test by taking theme distribution over moral foundation to build contingency tables separately for liberals and conservatives funding entities. Our test results show the p-value < 0.05 for both views. Therefore, we reject



(a) Timeline of Impressions and Spend



(b) Granger causality test

Fig. 10: (a) Per day impressions and spend for ads related to COVID vaccine. We also highlight important events related to COVID with vertical bar. (b) Granger causality tests comparing daily COVID deaths and ads impressions for each day on ‘encourage vaccination’, ‘vaccine mandate’, ‘government trust’, and ‘vaccine rollout’ themes. On the x -axis, we report the number of lags in days; on the y -axis, we show the sum-of-square F – test statistics for corresponding lag. We highlight those with p -value < 0.05 with black circle. Best viewed in electronic format (zoomed in).

the null hypothesis, indicating some association between theme and moral foundation.

After analyzing the messaging themes and moral foundations for different funding entities, the evidence indicates different groups are fulfilling different messaging roles (Answer to **RQ2**).

E. Targeted Demographics and Geographics

In our data, ads are more prominently viewed by females than the males from all age groups based on impressions. However, to answer **RQ3**, we further analyze the age and gender distribution over ad impressions on four messaging themes, i.e., encourage vaccination, vaccine mandate, government trust, vaccine rollout (Fig. 8). From Fig. 8 we see that more females from age group 25 – 34 view ‘encourage vaccination’ themed ads. Conversely, narratives belonging to ‘vaccine mandate’ and ‘government trust’ are viewed mostly by the older population. The largest gap between female and male views is found within the 65+ year-old category, whereas both males and females

from 25 – 34 age group equally view ads having ‘vaccine mandate’ narratives. On the other hand, more females from the age group 55 – 64 watch ads with ‘government trust’ theme and slightly more males than the females from the age group 35 – 44 view those ads. We notice more females than males from the age range 35 – 44 view ‘vaccine rollout’ themed ads and there is a significant gap between female and male views in this group. We perform t-test [62] hypothesis testing to provide statistical significance of our study. Table VIII shows the null hypothesis (H_0), alternate hypothesis (H_a), t-test statistics with p -value for each tested variables. We select level of significance, $\alpha = 0.05$. If p -value $< \alpha$, we reject H_0 ; otherwise we accept H_0 . No statistical significance is found when we test whether more females compared to males of older age (55+) watch ‘vaccine mandate’ and ‘government trust’ themed ads as p -value > 0.05 and we accept H_0 (Table VIII). We find highly statistically significant results (p -value < 0.01) when we test whether more females than the males of the age group 25 – 34

watch ads with ‘encourage vaccination’ theme and whether more females than the males of the age group 35 – 44 watch ‘vaccine rollout’ ads. For both tests p-value < 0.01 and we reject H_0 (Table VIII).

To understand how messaging changes based on geographic and demographics targeting, we choose two different age group 25 – 34 and age group 65+ from low vaccination rate state Wyoming and high vaccination rate state Massachusetts[§]. Fig. 9 shows that people from age range 25 – 34 watch ads having ‘encourage vaccination’ theme both in WY and MA. Our t-test results show statistical significance as p-value < 0.05 (Table VIII). On the other hand, the older population (65+) views narratives from ‘vaccine mandate’ ads both in WY and MA. But we do not find statistical significance for WY as p-value > 0.05 , and we accept the null hypothesis (Table VIII). For MA, we find statistical significance (p-value < 0.05).

F. Temporal Relationship with COVID Status

After analyzing the targeted demographics of the ads, we now move our attention to *when* the audience is exposed to them. Therefore, for the temporal evolution of these campaigns and the attention audiences receive, we look at the impressions and expenditure of ads over 2021 (Fig. 10a). It is clear that there was a noticeable spike of ad impressions on May 12th when CDC recommended Pfizer vaccine for adolescents age 12 and older. There was a significant increase in impressions on August 9th. It was after the day U.S. had seen more than 107,000 daily cases, the highest it had seen in six months. In addition, hospitalizations were the highest since February, with most occupants unvaccinated in August 7th[¶]. Spikes of impressions occurred after September 9th when Biden announced new COVID-19 vaccine mandates for federal workers, large employers and health care staff[¶]. A significant spike for expenditure was noticed after December 15th as COVID deaths in the United States surpassed 800,000^{**}.

Granger Causality with Daily COVID Death : As we observe large spikes, we ask whether ads impressions are more likely to follow newly COVID death status per day. To check this, we compute two time series:

- (1) For COVID daily death data, we consider the number of new COVID death per day called $Deaths(t)$ from data.cdc.gov.
- (2) For impressions, we calculate the total number of impressions of ‘encourage vaccination’, ‘vaccine mandate’, ‘government trust’, ‘vaccine rollout’ themed ads for a given day, $AdsImpressions(t)$.

We check stationarity for both time series using Augmented Dickey-Fuller test (ADF Test) [64]. As p-value < 0.05 for both time series, we reject the null hypothesis (H_0), the data does not have a unit root and is stationary. Then, we compute following two Granger causality tests with these two time series to check (1) Do $Deaths(t)$ Granger cause $AdsImpressions(t)$? (2) Do $AdsImpressions(t)$ Granger

cause $Deaths(t)$? The null hypothesis (H_0) assumed by the first test is that $Deaths(t)$ do not Granger cause $AdsImpressions(t)$ and the alternative hypothesis (H_A) is that $Deaths(t)$ Granger cause $AdsImpressions(t)$. For the second test, H_0 is $AdsImpressions(t)$ do not Granger cause $Deaths(t)$ and $H_A = AdsImpressions(t)$ Granger cause $Deaths(t)$. We reject H_0 if p-value is < 0.05 for these tests. We report results for these two tests in Fig. 10b. We notice a significant F-test for the hypothesis of $Deaths(t)$ Granger cause $AdsImpressions(t)$ (Right side of Fig. 10b) which answers **RQ4**. Conversely, we find no significant Granger causality from ads impressions on specific theme to daily new COVID death (Left side of Fig. 10b). Our finding from this analysis is when number of daily new COVID deaths changes, ads sponsored by the advertisers supporting specific theme get more attention.

VI. CONCLUSION

We suggest a minimally supervised multi-task learning framework for analyzing COVID-19 vaccine campaigns on social media. Also, by providing a novel dataset and set of themes and phrases to analyze ongoing vaccine campaigns on social media, we hope to help policymakers make better decisions on pandemic control. Our work has some limitations, such as restricting our attention to a specific use case of Facebook advertising: COVID vaccine related ads in USA. Another is transparency – some particular aspects of the advertising campaigns are not available to the public through the Facebook Ads Library API, thus limiting our findings. Despite these limitations, we believe our work brings essential elements to the debate on Facebook advertising in public health crisis. As we make our dataset available to the community, we hope the advertising domain will become a crucial part of public discourse on public health. This work is only the first step toward a more transparent campaign which we hope will continue.

VII. ETHICS STATEMENT

The data collected in the paper was made publicly available by Facebook Ads API. The data does not contain any personally identifying information. Our data reports engagement patterns at an aggregate level. Therefore, we do not derive or infer any potentially sensitive characteristics or health information that may violate users’ privacy. Our analysis is based on English-written ads focusing on the United States only, which may have unknown biases.

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[§]usafacts.org

[¶]www.voanews.com

[¶]www.whitehouse.gov

^{**}www.nytimes.com

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