Moral Narratives Around the Vaccination Discourse on the Facebook Platform

Extended Abstract

Vaccination hesitancy has been a threat to public health since a long time [Wolfe and Sharp, 2002], and it is currently being fueled by the large spreading of misinformation in many social media [Broniatowski et al., 2018]. Attitudes against vaccination usually rise around fake news or conspiracy theories, but according to moral psychology they are shaped by individual moral preferences. The Moral Foundations Theory (MFT) [Graham et al., 2013] explains individual variations in moral preferences using five dimensions (foundations): harm, fairness, loyalty, authority and purity, and it has been shown that these foundations underlie human judgements on politics, religion and social cooperation [Haidt, 2012; Curry, 2016]. In this work we assess the moral preferences expressed in the pro- and anti-vax discourses in a large dataset of Facebook comments. We show that significant differences exist in some moral dimensions between these two groups, and we suggest that these differences should be taken into account when designing vaccination campaigns.

Previous evidence that moral values are related to individual attitudes towards vaccination can be found in [Amin et al., 2017], where the authors used a sample of 1,000 parents in the US and found that parents with higher vaccine hesitancy tended to have higher levels of the purity and liberty foundations. Surprisingly, they also found that the harm/care foundation, traditionally addressed in vaccination campaigns, did not have a significant impact on vaccine hesitancy. A similar study by [Rossen et al., 2019] was performed in Australia based on an online questionnaire administered to 296 individuals. The authors found that vaccine rejecters showed significantly lower values of authority and significantly higher levels of purity, liberty and fairness.

Regarding the vaccination discourse in Facebook, [Klimuk et al., 2021] categorized a set of ≈ 20,000 comments about vaccination in Poland, and they found that the main categories related with vaccine hesitancy were—in decreasing order of importance—conspiracy theories, falsehoods, and concerns regarding safety and effectiveness of vaccines. Similar clusters were obtained by [Hoffman et al., 2019] with a sample of 197 individuals in Facebook in the US. Both works discuss narrative strategies to raise awareness on the importance of immunization.

The aim of this work is to provide more evidence on the impact of moral traits in vaccine hesitancy as expressed in social media, by analyzing a large volume of Facebook pages, posts and comments about vaccination. Though Facebook is currently diminishing its share in the social media landscape, it is still the most used social media in the general population and is a well-known target of misinformation campaigns [Allcott et al., 2019]. Recent efforts by Facebook
Table 1: Dataset statistics.

|                      | PRO-Vaccination pages | ANTI-Vaccination pages |
|----------------------|-----------------------|------------------------|
| Pages                | 101                   | 85                     |
| Original Posts       | 52,894                | 24,615                 |
| Original Comments    | 215,341               | 391,764                |
| Filtered Comments    | 170,954               | 286,111                |

Inc. to tackle fake news have certainly decreased their proliferation by adding a quality control. However, the large historical volume of posts and conversations remaining in many of its public pages constitutes a relevant source of data for studying the anti-vaccination discourse. Here we analyzed a set of 607,105 comments in 186 pro- and anti-vaccination pages in the period Jan, 2012-Jun 2019. A summary of the dataset is shown in the upper part of Table 1. As many posts bring up discussions between pro-vax and anti-vax users, we can find comments from both user groups interlaced among the replies. In order to tell apart both groups, we trained a classifier that, based on the comment’s text, can predict the type of attitude that it denotes: pro-vax, anti-vax or non-specified. Our classifier is composed of three parallel stages: an LSTM neural network, a named entity recognition stage based on TAGME [Ferragina and Scaiella, 2010] and a page class stage. The outputs are finally concatenated and used as input to a dense layer with a tanh activation function predicting which of the 3 groups the comment belongs to. The architecture, depicted in Figure FIG, was implemented in Keras [Chollet et al., 2015], and its design and configuration is inspired by [Lin et al., 2018]. The size of the LSTM hidden state was configured in 100 and the final dense layer has size 3. Words were transformed using the 100-dimensional pre-trained GloVe embeddings [Pennington et al., 2014].

The ground-truth for training was composed of 3000 comments which were manually tagged as pro-vax, anti-vax or non-specified. The cross-validated prediction results on this set are shown in Figure FIG (top-left) in terms of the ROC curve (Receiver Operating Characteristic). We chose the AUC measure as a metric for our model due to its high unbalance; The baseline accuracy for the area under this curve is 0.50, which represents the accuracy of a random classifier (coin flip). We obtained a cross-validated AUC (area under the ROC curve) of 0.84.

Table 2: Presence and polarity of the six moral foundations in the different comments groups (pro-vax, anti-vax, and non-relevant).

| Moral             | Presence (%) | Positive polarity (%) | Negative polarity (%) |
|-------------------|--------------|-----------------------|-----------------------|
|                   | PRO ANTI NON | PRO ANTI NON          | PRO ANTI NON          |
| Authority         | 51.34 50.83 14.66 | 39.79 31.57 13.59     | 32.64 44.57 7.43     |
| Liberty           | 22.84 26.23 18.13 | 36.47 45.96 25        | 11.98 4.93 6.54      |
| Loyalty           | 9.39 9.09 5.25  | 16.6 21.27 5.88       | 12.85 10.22 4.48     |
| Care              | 44.27 41.38 7.21 | 32.48 28.47 14.45     | 5.05 1.67 5.37       |
| Fairness          | 31.08 39.35 6.42 | 31.65 37.72 8.88      | 13.43 5.87 8.24      |
| Purity            | 31.09 22.64 26.52 | 13.04 12.54 19.22     | 31.5 15.91 49.23     |

Note. Values represent the percentage of comments that, being predicted as of that group (pro-vax, anti-vax, or non-relevant) express the respective moral.

We applied this trained model to the unlabeled part of the dataset, and performed a characterization of the moral traits expressed in pro- and anti-vax comments. For each pro- and anti-vax comment in the training set, we annotated the presence of each of the morals, and in case a moral was present, we annotated the polarity of its content (i.e., if the moral was positively and/or negatively expressed). For example, a comment expressing that “unvaccinated children shouldn’t be allowed to go to public school” has a negative polarity of the liberty foundation. Instead, a comment pointing out that “each person has the right to choose if they should be vaccinated” expresses the same moral, but with a positive polarity.

Using these samples, we trained one LSTM model for predicting the presence of each moral, and another one for predicting their positive and/or negative polarity. After applying the trained model to the full dataset, the percentage of
Figure 1: Performance of the models in terms of the Receiver Operating Characteristic curve and its AUC (area under the ROC curve).

Table 3: Accuracy of the LSTM predictors for each of the six moral foundations, expressed in terms of the area under the receiver operating characteristic (AUC).

| Moral presence | Positive polarity | Negative polarity |
|----------------|-------------------|-------------------|
| Authority      | 0.67              | 0.59              | 0.63              |
| Liberty        | 0.79              | 0.75              | 0.69              |
| Loyalty        | 0.57              | 0.55              | 0.53              |
| Care           | 0.70              | 0.61              | 0.46              |
| Fairness       | 0.63              | 0.65              | 0.51              |
| Purity         | 0.66              | 0.58              | 0.69              |

Comments predicted as expressing each moral is detailed in Table 2. The performance of the classifiers is shown in Table 3 in terms of the AUC and illustrated in Figure 1. We observe that some of the AUC’s are quite low (we consider that an AUC is acceptable if it is above 0.65, which represents a clear distinction from a random classifier). This might be due to the low number of training samples and the difficulty of the learning task (consider that the expression of a moral might be underlying and not quite explicit in a comment). However, among those morals whose prediction is acceptable, we observe that pro-vax comments are more commonly expressing anti-liberty arguments, while anti-vax comments express pro-liberty ones; also, these expressions are much more common than in comments predicted as non vaccination-related. We also observe that purity is expressed more frequently with a negative polarity by pro-vax comments than
by anti-vax comments. Interestingly, these two facts were precisely the ones found by [Amin et al., 2017] as the main differences in morals between pro-vax and anti-vax respondents in their study on vaccination hesitancy. Finally, and though not as significant as the previous ones, we find that pro-vax comments express more frequently a positive polarity of authority, while anti-vax comments express more frequently a negative value of it.

Indeed, several studies have shown that persuasive appeals in line with the moral traits endorsed by an audience can shift their attitudes on several issues. This kind of experiments framed by the Moral Foundations Theory has been performed, e.g., in the context of environmental consciousness [Feinberg and Willer, 2013; Kidwell et al., 2013] and donation to charities [Goenka and Van Osselaer, 2019].

We think that these results might help designing and framing vaccination campaigns by focusing on the liberty and authority traits (e.g., by remarking that vaccination gives people more freedom, by allowing them to perform their activities with safety, or by giving a clear picture of how scientific studies are validated and can be reproduced by peers). This can be of particular interest in the current COVID-19 pandemic context, in which misinformation campaigns are putting into risk the herd immunity goal and probably constitute the highest threat to global public health [Larson, 2018].

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