VIRATrustData: A Trust-Annotated Corpus of Human-Chatbot Conversations About COVID-19 Vaccines

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\section*{Abstract}
Public trust in medical information is crucial for successful application of public health policies such as vaccine uptake. This is especially true when the information is offered remotely, by chatbots, which have become increasingly popular in recent years. Here, we explore the challenging task of human-bot turn-level trust classification. We rely on a recently released dataset of observationally-collected (rather than crowdsourced) dialogues with VIRA chatbot, a COVID-19 Vaccine Information Resource Assistant. These dialogues are centered around questions and concerns about COVID-19 vaccines, where trust is particularly acute. We annotated 3\textsuperscript{k} VIRA system-user conversational turns for Low Institutional Trust (in context of the vaccine) or Low Agent Trust (towards the dialogue system) vs Neutral or High Trust. We refer to this dataset as VIRAT\textsuperscript{RUST}DATA and make it public as part of this paper. Then we demonstrate the utility of these annotations for building predictive models of trust.

\section{1 Introduction}
User’s trust is a critical component of effective communication (Mellinger, 1956). If dialogue systems are to become reliable and trustworthy sources of information, then modeling and understanding interlocutor trust is paramount. While there are a plethora of conversational agents for public health information about COVID-19, there have been no observational studies of user trust.

Turn-level user trust evaluation can be utilized in various ways. First, during the dialogue, it can be used to adjust a dialogue system’s responses or elicit human intervention. Post dialogue, it can (i) Assist in identifying topics or particular dialogue system responses inducing mistrust or improving trust; and (ii) Provide insight into the profile of people chatting with that certain dialogue system, that can drive improvement in the dialogue system’s design.

Importantly, trust is not sentiment. This may seem obvious, but negative sentiment towards COVID-19 is often opposed to vaccine hesitancy (hereafter, Low Institutional Trust). For instance, \textit{I'm young and healthy, I don't need the vaccine} presents a positive sentiment overall and a negative sentiment towards the vaccine, mapping to Low Institutional Trust. \textit{Where can I get a vaccine?} shows no explicit sentiment or stance toward vaccines, yet distinctly conveys high trust in the vaccine.

In this work, we explore the challenging task of human-agent turn-level trust classification, in the domain of COVID-19 vaccine-related conversations. We rely on real public dialogue system data, which is rarely available to the community due to the difficulty in collecting it and to privacy limitations in making it public.

The data, VIRADialogs (Gretz et al., 2022), contains 8\textsuperscript{k} conversations of actual users with VIRA – COVID-19 Vaccine Information Resource Assistant – a dialogue system which consults in a domain where trust is particularly acute. We annotated a subset of 3\textsuperscript{k} VIRA system-user conversational turns for Low Institutional Trust (in context of the vaccine) or Low Agent Trust (towards the dialogue system) vs Neutral or High Trust.

We refer to this dataset as VIRAT\textsuperscript{RUST}DATA and make it public as part of this paper. Then we demonstrate the utility of these annotations for building predictive models of trust.

\section{2 Background & Related Work}
\subsection{2.1 What is trust?}
Trust is multidimensional and different aspects of trust should be distinguished. We can decompose interpersonal trust into competence and benev-
olence, then these can be broken down further into more factors: competence, expertness, dynamism, predictability, goodwill/morality, goodwill/intentions, benevolent/caring/concern, responsiveness, honesty, credibility, reliability, openness/openmindedness, careful/safe, shared understanding, personal attractiveness (Mcknight and Chervany, 1996). Furthermore, we may also restate this as trust in intentions vs trust in beliefs.

The aforementioned definitions are mostly interpersonal (or in our case human-bot) relations; however, institutional trust is another construct which relates to a larger third party (Mcknight and Chervany, 1996; Harrison McKnight and Chervany, 2001; Watson, 2005). Here, institutional trust is the assumed (lack of) benevolence of institutions and (lack of) reliability of COVID vaccines.

2.2 Trust & Dialogue Systems

In the human-computer interaction (HCI) community there is work on human-computer trust (HCT) (Madsen and Gregor, 2000; Sebo et al., 2019; Gebhard et al., 2021). Notably, Madsen and Gregor (2000) make a similar distinction to ours, of trust towards the agent (micro trust) and institutional trust (macro-trust). This work then relates to a simpler measure of trust via desirability or perceived shared emotions (a.k.a. empathy) (Kraus et al., 2021).

Another active area of research is the language of chat systems that enhance user system trust (Gebhard et al., 2021; Zhou et al., 2019; Lukin et al., 2018), for instance the analysis of humor (Ritschel and André, 2018). Yet others have analyzed trust for customer service chatbots (Schanke et al., 2021). Our work instead focuses on annotating and modeling micro and macro trust on real observational data.

3 VIRAT RUST DATA Dataset

To create VIRAT RUST DATA, we annotated a subset of 3k user responses in VIRADialogs for institutional and agent trust level. Next, we describe the process of creating this dataset. We release VIRAT RUST DATA to the research community.

3.1 Data Selection and Pre-processing

First, we determined which user responses to label from VIRADialogs, as part of the Trust Labeling Task. We randomly sampled user responses under the following limitations:

1. Each dialogue in VIRADialogs contributed at most one turn.
2. Dialogues containing at least one user response marked with the is_profanity - indicating a toxic comment - were excluded.
3. Only user responses between 2 and 200 characters were included.
4. Only user responses containing alphabet letters were included.

As described in Gretz et al. (2022), user responses in VIRADialogs were modified to mask personal user information as well as toxic words. In addition, to facilitate annotators work, all occurrences of VIRA were replaced by 'chatbot'.

3.2 Trust Annotations Collection

To label user responses for trust, we conducted a crowd annotation task using the Appen platform.2 Annotators were presented with a single dialogue turn each time, consisting of a system message (for context), followed by a user response.

Annotators were asked two questions, directed at the user response. Question I was aimed at determining the perceived level of trust:

(1) What is the trust level reflected by the user response? [Options: Low trust, High trust, Not sure/Hard to tell]

Question II was a conditionally forking follow up to Question I (see Figures 1, 2 in Appendix). If a worker answered Low or High trust in Question I, Question II assessed the target of this perceived trust/mistrust:

(II.a) What is the main target of the user’s [trust/mistrust]? [Options: (i) The vaccine or related institutions/people; (ii) The chatbot]

To avoid annotator bias towards an answer that is not followed by an additional question, we included a follow up question if a worker first answered Not sure/Hard to tell:

(II.b) Does the user express any kind of sentiment? [Options: Yes, No]

Annotators were provided with examples for different possible answers (see Figure 3 in Appendix), as well as hidden embedded test questions, based on presumed ground truth. These question alerted annotators when they failed on them, hence provided additional feedback on task expectation while

2http://appen.com/
monitoring annotator quality, as detailed in Section 3.3.

Annotators were alerted that the task data may include toxic comments as well as misleading assumptions regarding COVID-19 vaccines. Each turn was annotated by 7 annotators. Annotators received $9/h on average, which is higher than the US minimum wage ($7.25).

3.3 Quality control

We employed the following measures for quality control:

(1) Test Questions - 25% of the questions answered by the annotators were hidden test questions based on ground truth. Annotators failing more than 30% of them were removed from the task and their annotations were discarded.

(2) Kappa Analysis - Following Toledo et al. (2019), we calculated (I) Annotator-κ: Pairwise Cohen’s kappa (κ) (Cohen, 1960) for each pair of annotators sharing at least 50 common judgements. We then averaged all pairwise κ for each annotator having at least 5 such pairwise κ values estimated. Annotations of annotators with Annotator-κ below 0.35 were discarded. (II) Task-Average-κ: Obtained by averaging Annotator-κ and is used to monitor task quality.

(3) Selected crowd annotators - Following Gretz et al. (2020), the task was available to a selected group of around 600 annotators who performed well on past tasks of our team.

Overall Trust Labeling Task Task-Average-κ on was 0.54 and 0.48 on Question I and Question II, respectively, which is reasonable for such subjective tasks (e.g., Ein-Dor et al. (2020)).

3.4 Post processing

To construct VIRATRUSTDATA from the annotations we collected, we filtered labels as follows:

(1) We only included turns in which at least 60% of annotators agreed on the majority label for Question I; (2) We further discarded turns in which the majority label for Question I was Low Trust, but no annotator majority was established for Question II label.

We define 4 classes for VIRATRUSTDATA:

Neutral - majority judgement on Question I was Not sure/Hard to tell;

High Trust - majority judgement on Question I was High Trust;

Low Institutional Trust - majority judgement on Question I was Low Trust and for Question II was The vaccine or related institutions/people;

Low Agent Trust - majority judgement on Question I was Low Trust and for Question II was The Chatbot.

Our data collection yielded 3,025 fully labeled system-user turns. The distribution of the classes as well as examples for them can be found in Table 1.

3.5 Data analysis

To examine the lexical characteristics of each of the 4 classes, we performed information-gain analysis. First, we lemmatized user responses, and kept lemmas with a word-frequency (wf) of at least 20 in each class. We then calculated the Kullback–Leibler (kl) divergence between lemma distribution over classes and prior classes distribution in the train set, and ranked the lemmas by their \(wf * kl\) score.

Table 2 presents the top ranked lemmas for each class, demonstrating the differences in class content. User responses labeled as Neutral for trust revolve around COVID-19 rather than the vaccines, with questions about variants and general immunity. Low Institutional Trust labeled responses discuss death (from the vaccine), side effects, and other harms that can be caused by the vaccine; whereas High Trust responses focus on boosters/shots (here in the verb form ‘shoot’) and where and when to get them.
Table 3: Evaluation of baselines over VIRATrustData. mac-F1 stands for macro F1 avg. and w-F1 stands for weighted macro F1 avg.

| Model        | overall | Low Inst. Trust | Low Agent Trust | Neutral | High Trust |
|--------------|---------|-----------------|-----------------|---------|-----------|
|              | acc     | mac-F1          | w-F1            | prec   | recall    | prec   | recall    | prec   | recall    |
| VANILLA-BERT | 0.873   | 0.716           | 0.873           | 0.840  | 0.823     | 0.350  | 0.222     | 0.893  | 0.911     |
| CT-BERT      | 0.898   | 0.762           | 0.888           | 0.846  | 0.883     | 0.650  | 0.311     | 0.910  | 0.915     |
| NB           | 0.766   | 0.573           | 0.754           | 0.751  | 0.596     | 1.000  | 0.111     | 0.769  | 0.901     |

4 Experiments

To report baseline results, we split the 3025 turns in VIRATrustData to 1816 for training, 301 for dev (used by neural models for early stopping) and 908 for testing, while preserving class distribution in all sets. For predicting trust-level we only used the user utterances.

4.1 Baselines Algorithms

We evaluated the following baselines:

- **NB** - Multinomial Naive Bayes, based on word count vectors.\(^4\)
- **VANILLA-BERT** - BERT-Large-uncased (Devlin et al., 2018), fine-tuned on the training set.
- **CT-BERT** (Müller et al., 2020) - A BERT-Large model pre-trained on 97M messages from twitter about COVID-19, fine-tuned on the training set.

The implementation details of both VANILLA-BERT and CT-BERT are in Appendix A.

4.2 Results

Results are presented in Table 3.\(^5\) CT-BERT performed best overall, as well as in the two most common classes, Low Institutional Trust and Neutral classes, demonstrating the advantage of domain adaptation. On High Trust, VANILLA-BERT provided the best recall, albeit with lower precision. All models struggled to detect Low Agent Trust, presumably as it is infrequent in the training set.

4.3 Error analysis

We reviewed 48 cases where all baselines predicted the labels incorrectly.\(^6\)

We identified 6 “incorrectly” labeled cases, due to borderline interpretation, such as “how safe are the vaccines” labeled as Low Institutional Trust.

Often, however, models failed on terms that required subtle context to disambiguate. E.g., Immune system was common in the Low Institutional Trust train set, but also in other classes, in the context of a compromised immune system and a question regarding a person that trusts their immune system. As such, “My immune system can deal with covid 19” is labeled by annotators as Low Institutional Trust, but is generally predicted as Neutral by the model. Other examples included are Neutral instances such as “Are there side effects” or “side effects Pfizer”, predicted as Low Institutional Trust by all models. However, these differ mostly in tone from true Low Institutional Trust examples (e.g., “Isn’t the vaccine unsafe because of side effects?”).

Low Agent Trust present is a different issue - it was under-predicted by all models due its low prevalence in the data. This was despite the fact that it is a relatively well defined class, usually containing direct reference to the dialogue system (e.g., “You are not answering my question...”, “who pays you?” etc.).

5 Conclusions

In this paper we highlight the need to detect Institutional/Agent low trust, reflected by users of public health chatbots. We implemented a corresponding crowd sourced annotation task, on top of VIRADialogs– a recently released dataset of real-world human-bot dialogues around COVID-19 vaccines. We share the VIRATrustData dataset, along with baseline results of several algorithms. We hope that this resource will be valuable to relevant research communities.

Future work should collect similar labeled data on domains beyond COVID-19 vaccines to support the development of more advanced models that detect Institutional/Agent Low Trust reflected by users.
Limitations

The dataset released in this paper presents a few limitations.

- The dataset covers a single domain, Covid-19 vaccine mistrust, with related unique attributes. Applying trust detection to other domains requires further data collection.

- The dataset was collected over months, hence it may have specific linguistic characteristics associated with this time period.

- Agent mistrust is rare in the given settings and therefore, underrepresented.

- Given that the annotation context for each input was a single dialogue turn, trust level may not always have been clear, and this might have led to an increase in the Neutral class ground truth. Notably, High Trust class ground truth is limited to inputs that clearly indicate a vaccinated user or a wish to be vaccinated.

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A Model Implementation Details

For both VANILLA-BERT and CT-BERT we use AdamW optimizer with a learning rate of $3 \times 10^{-5}$ and a batch size of 32. We fine-tune the model for 6 epochs and select the best performing checkpoint on the dev set according to overall accuracy. For CT-BERT we used COVID-Twitter-BERT v2.

![Figure 1: Trust Labeling Task interface, Low trust selection](https://huggingface.co/digitalepidemiologylab/covid-twitter-bert-v2)

![Figure 2: Trust Labeling Task interface, Not sure/Hard to tell selection](https://huggingface.co/digitalepidemiologylab/covid-twitter-bert-v2)

Figure 1: Trust Labeling Task interface, Low trust selection

Figure 2: Trust Labeling Task interface, Not sure/Hard to tell selection

![Figure 3: Trust Labeling Task Guidelines](https://huggingface.co/digitalepidemiologylab/covid-twitter-bert-v2)

Figure 3: Trust Labeling Task Guidelines

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1. https://huggingface.co/digitalepidemiologylab/covid-twitter-bert-v2

Examples

Chatbot: I hear you. Doctors say the main advantage of a vaccine is [...]  
User: I'm worried the vaccine will cause an adverse reaction  
Not sure / Hard to tell (user expresses a concern, not a certainty, regarding the vaccine)  
The user does express a sentiment (worry),

Chatbot: How can I help?  
User: Why do the covid vaccines kill people?  
The user has low trust (user assumes the vaccines are lethal)  
The main target of the user’s mistrust is the vaccine or related institutions/people.

Chatbot: Just like other vaccines, severe side effects are very rare [...]  
User: Can I take Tylenol after covid vaccine?  
The user has high trust (it is implied that this person intends to get a vaccination)  
The main target of the user’s trust is the vaccine or related institutions/people.

Chatbot: Hmnn... perhaps you can try to rephrase?  
User: you are a stupid AI robot  
The user has low trust (user claims chatbot is 'stupid')

NOTE:  
- Data for this task may include toxic comments  
- Data for this task may include misleading assumptions regarding COVID-19 vaccines