Decoding Susceptibility: Modeling Misbelief to Misinformation Through a Computational Approach

Anonymous ACL submission

Abstract

Susceptibility to misinformation describes the degree of belief in unverifiable claims, a latent aspect of individuals' mental processes that is not observable. Existing susceptibility studies heavily rely on self-reported beliefs, which can be subject to bias, expensive to collect, and challenging to scale for downstream applications. To address these limitations, in this work, we propose a computational approach to model users' latent susceptibility levels. As shown in previous research, susceptibility is influenced by various factors (e.g., demographic factors, political ideology), and directly influences people's reposting behavior on social media. To represent the underlying mental process, our susceptibility modeling incorporates these factors as inputs, guided by the supervision of people's sharing behavior. Using COVID-19 as a testbed domain, our experiments demonstrate a significant alignment between the susceptibility scores estimated by our computational modeling and human judgments, confirming the effectiveness of this latent modeling approach. Furthermore, we apply our model to annotate susceptibility scores on a large-scale dataset and analyze the relationships between susceptibility with various factors. Our analysis reveals that political leanings and psychological factors exhibit varying degrees of association with susceptibility to COVID-19 misinformation. [1]

1 Introduction

False claims spread on social media platforms, such as conspiracy theories, fake news, and unreliable health information. They mislead people's judgment, promote societal polarization, and exacerbate distrust in government (Pennycook and Rand, 2021; Nan et al., 2020). The harm is especially significant in various contentious events, including elections, religious persecution, and the global response to the COVID-19 pandemic (Ecker et al., 2022). Many works have investigated the *observable* behavior of misinformation propagation such as where the information propagates (Taylor et al., 2023), how people share it (Yang et al., 2020), and what people discuss about it (Gupta et al., 2022). However, it is still crucial but challenging to understand the *unobservable* mental and cognitive processes of how individuals believe misinformation (Ecker et al., 2022). Individual susceptibility (i.e., the likelihood of believing and being influenced by misinformation) plays a pivotal role in this context. If one is more susceptible to misinformation, they are not only more likely to share but also more prone to being misled by them (Scherer et al., 2020).

Previous works have investigated the psychological, demographic, and other factors that may contribute to the high susceptibility of an individual (Brashier and Schacter, 2020; Pennycook and Rand, 2017). However, these studies heavily rely on self-reported belief towards false claims collected from questionnaire-based participant surveys (Escolà-Gascón et al., 2021; Rosenzweig et al., 2021), which presents several limitations. For instance, different participants might interpret belief levels differently. Moreover, the data collection is labor-intensive, thereby limiting the scale of downstream research on the size, scope, and diversity of the target population (Nan et al., 2022).

People's mental processes, which are unobservable and influenced by various factors, directly affect several externalized behaviors, such as reposting on social media (Mitchell et al., 2019; Brady et al., 2020; Islam et al., 2020; Altay et al., 2022). Building on these prior works, we propose a computational method to model individuals' unobservable susceptibility levels, utilizing user-related factors and the supervision of their observable social media sharing behaviors. More specifically, our latent susceptibility modeling process uses a user's historical tweets as input to predict their sharing behavior

[1] We will release all the code used in our paper, along with our trained model and all collected data.

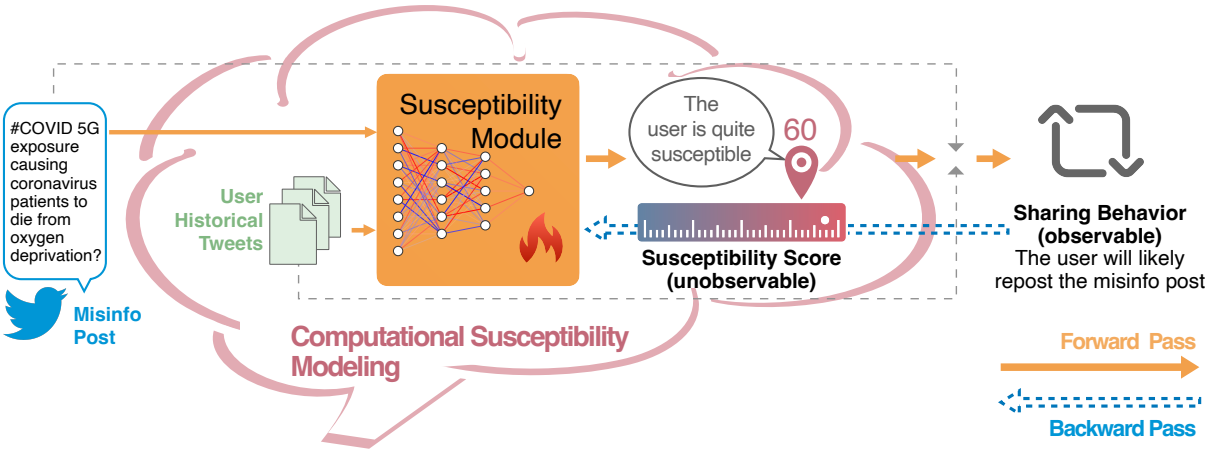

Figure 1: **Computational Modeling of Susceptibility to Misinformation**. We represent user susceptibility as a latent variable, which we capture using a shallow neural network. Our model is trained with the supervision of users' observable sharing behaviors, employing two loss functions: *binary classification entropy* and *triplet loss*.

for specific misinformation. We perform multi-task learning to simultaneously learn to classify whether a user would share a post, and rank susceptibility scores among similar and dissimilar users when the same content is seen. This computational modeling method unlocks the scales of misinformation-related studies and provides a novel perspective to reveal users' belief patterns.

In this paper, we focus our experiments on COVID-19 misinformation, and our evaluations demonstrate that the estimations from our model are highly aligned with human judgment when assessed through a susceptibility comparison task. We further employ our model to annotate susceptibility levels on a large-scale dataset. Building upon this extensive susceptibility labeling, we then conduct a set analysis to examine how various social factors relate to susceptibility. Our analysis reveals that psychological factors, professional fields, and political leanings are associated with susceptibility to varying degrees. Notably, this analysis, grounded in our inferred susceptibility scores, corroborates the findings of previous studies based on self-reported beliefs—for example, confirming that stronger analytical thinking is an indicator of lower susceptibility. Moreover, the results of our analysis show the potential to extend findings in the existing literature. For example, we demonstrate that the distribution of COVID-19 misinformation susceptibility in the U.S. exhibits a certain degree of correlation with political leanings. To sum up, our contributions are:

- We propose a computational model to infer people's susceptibility to misinformation by leveraging observable sharing activities to model unobservable latent susceptibility.
- Our evaluation demonstrates that our model effectively captures unobservable susceptibility levels, and its predictions on the susceptibility comparison task closely align with human judgment.
- We conduct a large-scale analysis to identify the underlying factors influencing susceptibility among a diverse user population, spanning various professional and geographical communities, thereby offering valuable insights for related social science research.

2 Related Work

Measure of Susceptibility The common practice to measure susceptibility is to collect self-reported absolute or relative agreement or disagreement with (or perceived accuracy, credibility, reliability, or validity of) one or more claims verified to be false from a group of individuals (Roozenbeek et al., 2020; Escolà-Gascón et al., 2021; Rosenzweig et al., 2021; Nan et al., 2022). A small number of previous studies indirectly assess the susceptibility by its impact, however, they can only capture behaviors rather than people's beliefs (Loomba et al., 2021). Cheng et al. (2021) defines a heuristic susceptibility score as the radio of misinformation posts out of all user's posts, which unrealistically simplifies the definition of susceptibility. Instead of using expensive and limited self-reported beliefs, we propose a computational model to estimate susceptibility at scale.

Contributing Factors and Application of Susceptibility Relying on the manually collected susceptibility annotation, previous research investigates the psychological, demographic, and more factors that contribute to users' susceptibility (Bringula et al., 2021; van der Linden, 2022). These factors include emotion (Sharma et al., 2022) (e.g. anger and anxiety; Weeks, 2015), analytic thinking (hui Li et al., 2022), partisan bias (Roozenbeek et al., 2022a), source credibility (Traberg and van der Linden, 2022), and repetition (Foster et al., 2012). Many theories have been proposed about the reason behind suscetibility (Scherer et al., 2020), including limited knowledge acquiring and literacies capabilities (Brashier and Schacter, 2020), strong preexisting beliefs (Lewandowsky and Ecker, 2012), neglecting to sufficiently reflect about the truth (Pennycook and Rand, 2017) or overconfidence (Salovich et al., 2020).

A better understanding of the phenomenon and mechanism of susceptibility can facilitate various downstream applications. These include analyzing the spread of bots (Himelein-Wachowiak et al., 2021), revealing community properties in information pathways (Taylor et al., 2023; Ma et al., 2023), combating misinformation by emphasizing publisher (Dias et al., 2020) and prebunking interventions based on inoculation (Roozenbeek et al., 2022b). However, the absence of a computational modeling framework significantly limits the scale of current susceptibility research.

Inferring Unobservables from Observables Latent constructs or variables refer to concepts that are not directly observable or measurable. Many studies have shown that unobservable variables can be inferred indirectly through models based on observable ones (Bollen, 2002; Borsboom et al., 2003). These unobservable variables can be estimated using various modeling techniques, including nonlinear mixed-effects models, hidden Markov models, or latent class models. In our work, we utilize a neural network-based architecture to model people's latent susceptibility level to misinformation, guided by the supervision provided by their observable sharing behaviors on social media.

3 Computational Susceptibility Modeling

Misinformation is characterized as information that is false, inaccurate, or misleading, which could be created deliberately or accidentally (Pennycook and Rand, 2021). The susceptibility to misinformation represents the belief in misinformation and related constructs, including discernment between true and false claims and the extent to which exposure to misinformation misleads subsequent decisions (Nan et al., 2022). Believing a piece of misinformation can influence various outward behaviors, such as sharing actions. Previous studies, like the inattention or "classical reasoning" account, contend that people are committed to sharing accurate information, but the unique context of social media disrupts their capacity to critically assess the accuracy of news (Pennycook and Rand, 2021; van der Linden, 2022). These studies suggest that people are more likely to share things they genuinely believe (Altay et al., 2022).

Inspired by the existing studies indicating that believing is an essential driver for dissemination, we propose to model the latent susceptibility, which reflects people's beliefs, with supervision from the sharing behaviors, while considering characteristics of the sharing content and user representation. We introduce a computational model to infer a user's unobservable susceptibility level based on their historical activities (§3.1) as shown in Fig. 1. We train the model with signals from the observable sharing behaviors on social media(§3.2), utilizing the constructed approximate contrastive user-post pairs as the training data (§4).

3.1 Modeling Unobservable Susceptibility

Content-Sensitive Susceptibility We compute the susceptibility of user u when a particular piece of misinformation p is perceived (i.e. $s_{u,p}$). This allows us to account for the fact that an individual's susceptibility can vary across different content, influenced by factors such as topics and linguistic styles. By focusing on the susceptibility to specific pieces of misinformation, we aim to create a more nuanced, fine-grained, and accurate representation of how users interact with and react to different misinformation.

User and Misinfo Post Embeddings As a component of the computational model, we use SBERT (Reimers and Gurevych, 2019), which is developed upon RoBERTa-large (Liu et al., 2019), to compute the embedding vector to represent the semantic information contained in the misinformation and user historical posts. We consider the misinformation post as a sentence and produce its representation with SBERT. For the user embedding, we calculate the average of sentence repre-

sentations for the user's recent original posts. More specifically, for every user-post pair (u, p), we gather the historical posts written by user u within a 10-day window preceding the creation time of the misinformation post p, to learn a representation of user u at that specific time.[2]

Computational Model for Susceptibility Given the input of user historical posts for the user u and the content for misinformation post p, the susceptibility computational model is expected to produce the *susceptibility score* $s_{u,p}$ as shown in Eq. 1, reflecting the susceptibility of u when p is perceived.

$$s_{u,p} = suscep(E(u), E(p)) \tag{1}$$

We first obtain the embeddings $E(p)$ and $E(u)$ for post p and user u, where u is represented by the user's historical tweets and E is the frozen SBERT sentence embedding function. The susceptibility score is calculated by the function $suscep$, which is implemented as a multi-layer neural network, taking the concatenation of the user and post embeddings as inputs. During the training phase, we maintain the sentence embedder as a fixed component and exclusively train the weights for the $suscep$ function. Then the learned $suscep$ function can be applied to generate susceptibility scores for new pairs of users (u) and posts (p) during the inference process.

3.2 Training with Supervision from Observable Behavior

Susceptibility is a latent variable and cannot be directly observed. Consequently, it is impractical to directly apply supervision to $s_{u,p}$ since only the user u themselves know their own beliefs regarding content p. To address this challenge, we regard susceptibility as a crucial factor for sharing behavior and train the susceptibility computational model using the supervision signals obtained from the observable behavior of sharing misinformation.

To determine the probability of user u sharing post p, we compute the dot product of the embeddings of the user and post content, incorporating the susceptibility score for the same pair of u and p estimated by our model as a weighting factor, and pass the resulting value through a sigmoid function, as illustrated in (2).

$$p_{\text{rp}} = \sigma\left(E(u) \cdot E(p) \cdot s_{u,p}\right) \tag{2}$$

It is important to highlight that we do not directly utilize the *susceptibility score* to estimate sharing probability because sharing behavior depends not solely on susceptibility levels but also on various potential confounding factors. For instance, it is possible that a user may possess a significantly high susceptibility score for a piece of misinformation but decides not to share it, potentially influenced by factors such as their personality, the impact of social influence, concerns about potential repercussions, and their emotional state at that specific moment, among other variables. To account for these potential confounding factors as comprehensively as possible, we incorporate a dot product of the user and post embeddings into our model.

Objectives To better train our computational model, we perform multi-task learning to utilize different supervision signals. First, we consider a binary classification task of estimating repost or not with a cross-entropy loss. Additionally, we perform the triplet ranking task (Chen et al., 2009; Hoffer and Ailon, 2014) to distinguish the subtle differences among the susceptibility scores of multiple users when the same false content is present.

During each forward pass, our model is provided with three user-post pairs: the anchor pair (u_a, p), the similar pair (u_s, p), and the dissimilar pair (u_{ds}, p). We regard the similar user u_s as the user who reposted p if and only if user u_a reposted p. The dissimilar user u_{ds} is defined by reversing this relationship. When multiple candidate users exist for either u_s or u_{ds}, we randomly select one. However, if there are no suitable candidate users available, we randomly sample one from the positive (for "reposted" cases) or negative examples (for "did not repost" cases) and pair this randomly chosen user with the misinformation post p.

In Eq. 3, we define our loss function. Here, y_i takes the value of 1 if and only if user u_i reposted misinformation post p. The parameter α corresponds to the margin employed in the triplet loss, serving as a hyperparameter that determines the minimum distance difference needed between the anchor and the similar or dissimilar sample for the loss to equal zero. Besides, λ is the control hyperparameter, which governs the weighting of the binary cross-entropy and triplet loss components.

[2]We chose the 10-day timeframe because it provides a substantial amount of data to represent a user and is also recent enough to capture their dynamics.

$$
\begin{aligned}
\mathcal{L}_{\text{bce}}(u_i, p) &= -\left(y_i \log(p_{\text{rt}}(u_i, p)) + (1 - y_i) \log(1 - p_{\text{rt}}(u_i, p))\right) \\
\mathcal{L}_{\text{triplet}}(u_a, u_s, u_{ds}, p) &= \text{ReLU}(\|s_{u_a,p} - s_{u_s,p}\|_2^2 - \|s_{u_a,p} - s_{u_{ds},p}\|_2^2 + \alpha) \\
\mathcal{L}(u_a, u_s, u_{ds}, p) &= \frac{\lambda}{3} \sum_{i \in \{a,s,ds\}} \mathcal{L}_{\text{bce}}(u_i, p) + (1 - \lambda)\mathcal{L}_{\text{triplet}}(u_a, u_s, u_{ds}, p) \qquad (3)
\end{aligned}
$$

4 Dataset and Experiment Setup

We have chosen Twitter as our data source because it hosts an extensive and diverse collection of users, the accessibility of its data, and its popularity for computational social science research (Zhang and Counts, 2015). Furthermore, Twitter offers users the freedom for free-text personal and emotional expression, with crucial metadata, including timestamps and location data, which are useful for our subsequent analytical endeavors.

Misinformation Tweets We consider two misinformation tweet datasets: the `ANTi-Vax` dataset (Hayawi et al., 2021) was collected and annotated specifically for COVID-19 vaccine misinformation tweets. And `CoAID` (Covid-19 Healthcare Misinformation Dataset; Cui and Lee, 2020) encompasses a broader range of misinformation related to COVID-19 healthcare, including fake news on websites and social platforms. The former dataset contains 3,775 instances of misinformation tweets, while the latter contains 10,443. However, a substantial number of tweets within these two datasets do not have any repost history. Hence, we choose to retain only those misinformation tweets that have been retweeted by valid users. Finally, we have collected a total of 1,271 misinformation tweets for our study.

Positive Examples We define the positive examples for modeling as (u_{pos}, p) pairs, where user u_{pos} viewed and retweeted the misinformation post p. We obtained all retweeters for each misinformation tweet through the Twitter API.

Negative Examples Regarding negative examples, we define them as (u_{neg}, p) pairs where user u_{neg} viewed but did not retweet misinformation post p. However, obtaining these negative examples poses a considerable challenge, because the Twitter API does not provide information on the "being viewed" activities of a specific tweet. To address this issue, we construct potential negative users u_{neg} who are highly likely to have viewed a particular post p but did not repost it, following these heuristics: 1) u_{neg} should be a follower of the author of the misinformation post p, 2) u_{neg} should not retweet p, and 3) u_{neg} was active on Twitter within 10 days before and 2 days after the timestamp of p.

	Total	Positive	Negative
# Example	7658	3811	3847
# User	6908	3669	3255
# Misinfo tweet	1271	787	1028

Table 1: **Data Statistics** of our constructed training dataset. We show the statistics for the number of the user-tweet pairs (*# Example*), unique users (*# User*), and unique misinformation tweets (*# Misinfo tweet*) in the overall dataset and the positive and negative subsets.

In the end, we collected 3,811 positive examples and 3,847 negative examples, resulting in a dataset consisting of a total of 7,658 user-post pairs. We divide the dataset into three subsets with an 80% - 10% - 10% split for train, validation, and test purposes, respectively. The detailed statistics of the collected data are illustrated in Tab. 1. We provide the training details of our model in Appendix A.

5 Evaluation

We demonstrate the effectiveness of our susceptibility modeling by directly comparing our estimations with human judgment (§5.1) and indirectly evaluating for assessing sharing behavior (§5.2, §5.3).

5.1 Validation with Human Judgement

Due to the abstract nature of susceptibility and the absence of concrete ground truth, we encounter challenges in directly assessing our susceptibility modeling. As a result, we tend to human evaluations to validate the effectiveness of our modeled susceptibility. Given the inherent subjectivity in the concept of susceptibility, and to mitigate potential issues arising from variations in individual evaluation scales, we opt not to request humans to annotate a user's susceptibility directly. Instead, we structure the human evaluation as presenting human evaluators with pairs of users along with their historical tweets and requesting them to determine which user appears more susceptible to overall COVID-19 misinformation. We provide

more details regarding the human judgment framework and the utilized interface in Appendix B.

Subsequently, we compared the predictions made by our model with the human-annotated predictions. To obtain predictions from our model, we compute each user's susceptibility to overall COVID-19 misinformation by averaging their susceptibility scores to each COVID-19 misinformation tweet in our dataset. As presented in Tab. 2, our model achieves an agreement of 72.90% with human predictions, indicating a solid alignment with the annotations provided by human evaluators. Additionally, we consider a baseline that directly calculates susceptibility scores as the cosine similarity between the user and misinformation tweet embeddings. Compared to this baseline, our susceptibility modeling brings a 9.35% improvement. Moreover, we conduct a comparison with ChatGPT by providing it with instructions based on the task description of the susceptibility level comparison setting in a zero-shot manner (more details are in Appendix D). We notice that our model even outperforms predictions made by ChatGPT, despite ChatGPT being a significantly larger model than ours. These results of the human judgment validate the effectiveness of our proposed susceptibility modeling, showcasing its capability to reliably estimate user susceptibility to COVID-19 misinformation.

	Our	Baseline	ChatGPT
Agreement	72.90	63.55	62.62

Table 2: **Comparison with Human Judgement**. `Baseline` refers to a direct comparison based on cosine similarity between user and misinformation embeddings, while `ChatGPT` denotes prompting the ChatGPT model (engine *gpt-3.5-turbo*) for determining the more susceptible user in a zero-shot manner.

5.2 Inferred Susceptibility Score Distribution

We provide a visualization showing the distribution of susceptibility scores produced by our model for both the positive and negative examples within the training data. As illustrated in Fig. 2, there is a significant disparity in the distribution between positive and negative examples. The difference in the means of the positive and negative groups is statistically significant, with a p-value of less than 0.001. This confirms our assumption that the susceptibility level to misinformation is a fundamental influencing factor for subsequent sharing behavior.

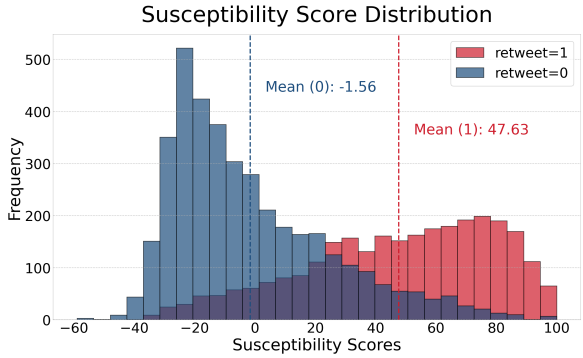

Figure 2: **Susceptibility Score Distribution** among positive and negative user-tweet pairs. The distribution of susceptibility levels, estimated by our computational modeling, among positive (red) and negative (blue) examples exhibits a significant difference.

5.3 Resulting Sharing Behavior Prediction

Additionally, as described in §3, a high susceptibility level to misinformation is highly likely to lead to subsequent sharing behavior on social media. Here, we reinforce this assumption by showcasing that our learned susceptibility model exhibits a strong capability to predict subsequent sharing behavior. When tested on the held-out test set, our model achieves a test accuracy of 78.11% and an F1 score of 77.93. These results indirectly demonstrate the validity of our computational modeling for latent susceptibility within the human thought process.

6 Analysis

Furthermore, we demonstrate in this section the potential of our proposed computational susceptibility modeling in expanding the scope of susceptibility-related research. Our analysis not only aligns with the findings of previous survey-based studies (§6.1) but also goes a step further by extending and enriching their conclusions (§6.2).

6.1 Correlation with Psychological Factors

Previous research on human susceptibility to health and COVID-19 misinformation primarily relied on questionnaire surveys (Scherer et al., 2020; Nan et al., 2022; van der Linden, 2022). These studies have identified several psychological factors that influence individuals' susceptibility to misinformation. For instance, analytical thinking (as opposed to intuitive thinking), trust in science, and positive emotions have been linked to a greater resistance to health misinformation. Conversely, susceptibility to health misinformation is frequently associated with factors such as conspiracy thinking, religios-

Factors	Coeff.	Factors	Coeff.
Analytic Thinking	-0.31	Emotion - Positive	-0.08
Political Leaning	0.13	Emotion - Anxious	0.08
Ethnicity	0.09	**Emotion - Angry**	0.16
Religiosity	0.10	**Emotion - Sad**	0.14
Technology	-0.09	**Swear**	0.18
Illness	0.09	Wellness	-0.02

Table 3: **Correlation Coefficients** between our modeled susceptibility levels and various psychological factors. Our model reveals correlations that are consistent with findings from prior questionnaire-based health susceptibility studies. The factors with absolute scores greater than 0.1 are highlighted in red (+) and blue (-).

ity, conservative ideology, and negative emotions. In this part, we analyze the correlation coefficients between our modeled susceptibility scores and the aforementioned factors to determine whether our results align with previous research findings.

To achieve this, we compute factor scores for each user in our dataset based on their historical tweets using LIWC Analysis.[3] We mainly consider the following factors: *Analytic Thinking*, Emotions (*Positive* emotions, *Anxious*, *Angry* and *Sad*), *Swear*, *Political Leaning*, *Ethnicity*, *Technology*, *Religiosity*, *Illness* and *Wellness*. These factors have been extensively studied in previous works and can be inferred from a user's historical tweets. We calculate and plot the Pearson correlation coefficients between each factor and the susceptibility level estimated by our model in Tab. 3.

In our analysis, the correlations are consistent with findings from previous social science studies that relied on surveys to assess participants' health susceptibility. For instance, *Analytic Thinking* is a strong indicator of low susceptibility, with a correlation coefficient of -0.31. Conversely, certain features such as *Swear*, *Political Leaning*, and *Angry* exhibit a weak correlation with a high susceptibility level. These results not only corroborate the conclusions drawn from previous questionnaire-based studies (van der Linden, 2022; Nan et al., 2022) but also provide further validation for the effectiveness of our computational modeling for susceptibility.

6.2 Community Differences

We further leverage our computational model to investigate how susceptibility level differs and compares between different community groups on social networks. Specifically, two different types of communities are considered: professional and geographical communities.

To perform a reliable analysis among different communities, a large-scale user dataset is needed. To address this requirement, we sample 100,000 users across the world from the existing COVID-19 Tweet Dataset (Taylor et al., 2023) which contains all COVID-19-related tweets for a certain time. [4] Furthermore, for better interpretability, we normalize the resulting susceptibility scores within the range of -100 to 100 using *Min-Max* normalization. We define -100 to indicate that the individual holds the most resistance to misinformation, while 100 means the individual is easiest to believe in misinformation when encountered. To obtain an aggregated susceptibility score for a community, we calculate the mean of individual susceptibility scores for all users within that community.

Occupation and Professional Community We first explore how susceptibility varies among users with different occupations. There is a social consensus regarding the susceptibility of the practitioners within a specific occupation community. For example, susceptibility scores towards health misinformation are expected to be significantly lower among experts in health-related fields compared to the general population (van der Linden, 2022; Nan et al., 2022). We consider the following professional communities and compare their average susceptibility scores: Education (*Edu*), Society and Public (*S&P*), Health and Medicine (*H&M*), Finance and Business (*F&B*), Science and Technology (*S&T*), Arts and Media (*A&M*), as well as *N/A* for Twitter users who do not specify their occupation in their user descriptions.

The results are presented in Tab. 4. It is worth noting that professions closely associated with *S&T*, *H&M*, and *Edu* tend to exhibit lower susceptibility to COVID-19 misinformation. In contrast, occupations within the *A&M* area demonstrate comparatively higher susceptibility, possibly because of their greater exposure to misinformation and stronger emotional reactions. These findings align with our expectations and reinforce the previous conclusions that expertise and knowledge in

[3] liwc.app. For each user, we compute the final factor score by calculating the average value across the user's historical tweets. However, for emotional factors like anxiety and anger, which may appear less frequently, we choose to use the maximum value instead to better capture these emotions.

[4] Besides, we make sure each sampled user has posted more than 100 historical tweets between January 2020 and April 2021. For each user, we utilize the Twitter API to gather their user descriptions and location information, after which we extract and categorize their occupations from their self-reported descriptions with ChatGPT in a zero-shot manner.

relevant fields serve as protective factors against misinformation (Nan et al., 2022)[5].

Occupation	Suscep.	# Users
N/A	4.6201	35145
Arts and Media	-0.1504	12635
Science and Technology	-2.2076	7170
Finance and Business	-5.4192	5844
Health and Medicine	-5.4762	6272
Society and Public	-6.7747	10973
Education	-7.8070	5261

Table 4: **Susceptibility Distribution by Professional Field**. We present the average susceptibility scores, estimated by our computational modeling, for 6 main professional fields. *S&T*, *H&M*, and *Edu* (highlighted in blue) tend to have lower susceptibility to COVID-19 misinformation, consistent with existing studies.

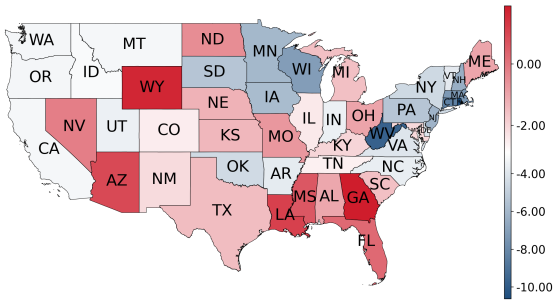

Figure 3: **Susceptibility Distribution by U.S. State**. We plot the susceptibility score, estimated by our computational modeling (with Bayesian smoothing), for each state in the U.S. The average susceptibility score in the overall U.S. (-2.87) is used as the threshold, with scores above it displayed in red, and those below it in blue. Due to insufficient data points, we are only displaying data for 48 contiguous states within the U.S.

Geographical Community We further investigate the geographical distribution of susceptibility to COVID-19 misinformation, specifically focusing on different U.S. states.[6] This analysis enables us to explore the influence of political ideology associated with different U.S. states (Gelman, 2008) on susceptibility to misinformation. Out of the 100,000 users sampled from around the world, 25,653 users are from U.S. states with more than 200 users for each state. As shown in Fig. 3, the distribution of susceptibility levels estimated by our computational modeling is imbalanced across U.S. states and demonstrates a certain degree of correlation with political leanings. In general, states known to have a more conservative population tend to have relatively higher susceptibility scores, while states that are considered more liberal have lower scores. The average susceptibility score for users in blue or red states is -3.66 and -2.82 respectively.[7] We observe that 60% of the ten states with the highest susceptibility scores are red states, and 90% of the ten states with the lowest susceptibility scores are blue states. This trend corresponds with the conclusion observed in various previous studies, where political ideology influences people's perspectives on scientific information (McCright et al., 2013; Baptista et al., 2021; Imhoff et al., 2022). However, it is important to acknowledge the limitations of our analysis, as it solely reflects the estimated susceptibility distribution of the sampled users within each state. In Appendix E, we present the average susceptibility scores calculated based on our sampled users for each U.S. state, along with the corresponding number of users.

7 Conclusion

In this work, we propose a computational approach to model people's latent susceptibility to misinformation. While previous research on susceptibility is heavily based on self-reported beliefs collected from questionnaire-based surveys, our model trained in a multi-task manner can estimate user's susceptibility levels with supervision from their sharing behavior on social media. When compared with human judgment, our model shows highly aligned predictions on a susceptibility comparison evaluation task. To demonstrate the potential of our proposed computational modeling in extending the scope of previous misinformation-related studies, we leverage the susceptibility scores estimated by our model to analyze factors that influence susceptibility to COVID-19 misinformation. Our analysis considers a diverse population from various professional and geographical backgrounds, and the results obtained through our computational modeling not only align with but also support and extend the findings from previous survey-based social science studies.

[5]We notice that Twitter users who don't declare their occupation in their user description (*N/A*) exhibit a higher susceptibility to COVID misinformation. This may be because those who are willing to declare their profession are often public figures who care more about their reputation.

[6]Given the imbalance in the number of users from different U.S. states, we calculate average susceptibility scores for each state with Bayesian smoothing. We use the overall mean and overall standard deviation as priors, and the more users in the state, the less the overall mean will affect that state's score.

[7]Red and blue states are determined by the 2020 presidential election results, with red states leaning Republican and blue states leaning Democratic.

Limitations

Besides investigating the underlying mechanism of misinformation propagation at a large scale, the susceptibility scores estimated by our model have the potential to be used to visualize and interpret individual and community vulnerability in information propagation paths, identify users with high risks of believing in false claims and take preventative measures, and use as predictors for other human behaviors. However, while our research represents a significant step in computational modeling susceptibility to misinformation, several limitations should be acknowledged.

First, our model provides insights into susceptibility based on the available data and the features we have incorporated. However, it's important to recognize that various other factors, both individual and contextual, may influence susceptibility to misinformation. These factors, such as personal experiences and offline social interactions, have not been comprehensively incorporated into our modeling and should be considered in future research.

Moreover, our modeled susceptibility scores represent an estimation of an individual's likelihood to engage with misinformation. These scores may not always align perfectly with real-world susceptibility levels. Actual susceptibility is a complex interplay of cognitive, psychological, and social factors that cannot be entirely captured through computational modeling. Our modeling should be viewed as a valuable tool for identifying trends and patterns, rather than as a means for providing definitive individual susceptibility assessments.

Finally, our study's findings are based on a specific dataset and may not be fully generalizable to all populations, platforms, or types of misinformation. Especially when examining the geographical distribution of susceptibility, it's important to note that not all U.S. states have a sufficient amount of Twitter data available for analysis, due to the high cost of data collection. Furthermore, platform-specific differences and variations in the types of misinformation can potentially impact the effectiveness of our modeling and the interpretation of susceptibility scores.

Ethics Statement

Analyzing and modeling susceptibility to misinformation can potentially raise several ethical concerns, particularly when applied at an individual level. Due to its dual nature, our modeling can not only be used to identify users with a high risk of believing in misinformation and taking preventative measures to reduce harm, but it also holds the potential for misuse by malicious actors, leading to privacy violations, stigmatization, and targeted attacks. To minimize the risk, we refrained from using any personally identifiable information (PII) data in our work. Nevertheless, it remains important to carefully consider the ethical implications associated with the deployment of computational models like ours, enhance regulatory oversight, and ensure responsible and transparent utilization.

We acknowledge the need for ongoing ethical scrutiny and are committed to the responsible release of our trained model, and this includes requiring users to sign a Data Use Agreement that explicitly prohibits any malicious or harmful use of our model. Within this agreement, researchers and practitioners will also be required to acknowledge the limitations (§7), that our modeling may not fully or accurately represent an individual's real susceptibility level.

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A Training Details

We use the *sentence-transformers/all-roberta-large-v1* model from `sentence-transformers` as our sentence embedder. Through grid search on learning rates ranging from 1e-5 to 5e-4 and λ values from 0 to 1, we train our model using a learning rate of 3e-5, set the hyperparameter λ to 0.9, and the margin α to 1 for 100 epochs on the training set, as detailed in §3. Following the training process, we select the checkpoint with the lowest validation loss and proceed to evaluate its performance on the test set.

B Human Judgement

Here, we provide details about the human judgment framework utilized in our work.

During human judgment, annotators are tasked with selecting the more susceptible user based on five historical tweets for each user. We offer the user interface used for human judgment in Figure 4. In the task description, susceptibility is described as being more likely to believe, be influenced by, and propagate COVID-19 misinformation. To account for annotator uncertainty, we provide four options: *Definitely User A*, *Probably User A*, *Definitely User B*, and *Probably User B*. Furthermore, we also request annotators to identify the "most susceptible tweet" for the selected user, to enhance the reliability of annotations. This tweet should best exemplify the user's susceptibility to COVID-19 misinformation or be the basis for the annotator's decision.

Also, it is important to note that even when both users seem to have low susceptibility to COVID-19 misinformation, we still ask the annotator to make a choice. This is because our goal is to rank users based on their relative susceptibility, offering a comparative assessment rather than an absolute determination.

In total, we randomly sampled 110 user pairs and collected three annotations for each user pair. We recruited human annotators from Amazon Mechanical Turk (AMT) in the U.S. and compensated each annotator with $0.5 (hourly wage higher than the federal minimum wage). To determine the gold label for each user pair, we applied a weighted majority voting approach, assigning a value of 0.5 to *Probably User X* and a value of 1 to *Definitely User X*. We excluded user pairs with tied annotations, resulting in a final dataset of 107 user pairs. The kappa score for interrater agreement among the annotators is 0.74.

C Examples of User Posts and Susceptibility Scores

The user `KatCapps`'s susceptibility score is estimated as `38.62` when the user sees the tweet:

> The coronavirus infection rate is still too high. There will be a second wave | David Hunter [Link]

History tweets posted by the user are:

- RT @gregggonsalves: Study estimates 24 states still have uncontrolled coronavirus spread
- RT @JoeSudbay: OSHA chas not issued enforceable guidelines for protecting employees from covid-19, as it did during the H1N1 outbreak in
- RT @mlipsitch: New Oped with @rickmalley | Treating Mild Coronavirus Cases Could Help Save Everyone - The New York Times
- RT @stevesilberman: Texas church that rushed to reopen cancels masses after priest dies and others contract #coronavirus.
- RT @carlzimmer: Several cases of coronavirus reported after a swim party in Arkansas, governor says
- RT @GlennKesslerWP: They Survived the Worst Battles of World War II. And Died of the Virus.

Another user `AmitSin91018424`'s susceptibility score is estimated as `-12.27` when the user sees the tweet:

> Dominic Cummings has broken Covid-19 policy trust, say top scientists [Link]

History tweets posted by the user are:

- RT @guardian: The pandemic has laid bare the failings of Britain's centralised state | John Harris
- RT @guardian: Coronavirus world map: which countries have the most cases and deaths?

D ChatGPT Prompt Template

In Fig. 5, we present the template used to prompt ChatGPT for the susceptibility comparison task (§5.1).

E Average Susceptibility Scores and User Counts by U.S. State

We provide the aggregated susceptibility scores estimated by our computational modeling for each U.S. state (§6.2), along with the number of sampled users in Tab. 5.

Comparing Susceptibility to COVID-Related Misinformation

In this task, you will be presented with 2 Twitter users, each with 5 historical tweets presented in chronological order. Your objective is to determine which of the two users is more susceptible to COVID-related misinformation, which we define as being more likely to believe, be influenced by, and propagate such misinformation, e.g. through retweeting.

User A's Historical Tweets:

○ ${A_1}
○ ${A_2}
○ ${A_3}
○ ${A_4}
○ ${A_5}

User B's Historical Tweets:

○ ${B_1}
○ ${B_2}
○ ${B_3}
○ ${B_4}
○ ${B_5}

You have four options to choose from:

○ Definitely User A

○ Probably User A

○ Probably User B

○ Definitely User B

Choose option Definitely User A or Definitely User B, if you are highly confident that this user is more susceptible. And please choose option Probably User A or Probably User B, if you believe this user is more susceptible, but you are not entirely sure. It's necessary to make a choice even if both users appear to have low susceptibility to COVID misinformation. In such cases, you must select the user who, in your judgment, is relatively more susceptible.

Additionally, you are also tasked with selecting the most "susceptible" tweet for the user you have identified as more susceptible. This tweet should best reflect the user's susceptibility to COVID misinformation or be the tweet upon which you based your decision.

Figure 4: **Human Judgement Interface** utilized in our work. Participants are instructed to select the more susceptible user from a user pair based on five historical tweets for each user.

```
In this task, you will be presented with 2 Twitter users, each with 5 historical tweets presented in
chronological order. Your task is to determine which of the two users is more susceptible to COVID-
related misinformation, which we define as being more likely to believe, be influenced by, and
propagate such misinformation, e.g. through retweeting.

User A's Historical Tweets:
{userA_text}

User B's Historical Tweets:
{userB_text}

It is necessary to make a choice even if both users appear to have low susceptibility to COVID
misinformation.
In such cases, you must select the user who, in your judgment, is relatively more susceptible.

Please answer with one of the following options without any other text: A | B.
```

Figure 5: **ChatGPT Prompt Template** for the susceptibility comparison task.

State	Suscep.	# Users	State	Suscep.	# Users
Georgia	0.3935	669	Idaho	-3.2296	265
Florida	-0.2404	1592	Washington	-3.2577	526
Arizona	-0.5566	499	Montana	-3.2590	543
Louisiana	-1.3878	202	Oregon	-3.2612	260
Ohio	-1.6120	679	Utah	-3.3324	206
Texas	-1.7478	1627	Vermont	-3.3548	556
Missouri	-1.9076	308	Indiana	-3.3901	270
Nevada	-1.9857	294	Delaware	-3.4139	359
Michigan	-2.0996	575	Arkansas	-3.4179	418
Alabama	-2.3902	377	North Carolina	-3.5324	635
Maryland	-2.4763	527	South Dakota	-3.6020	351
South Carolina	-2.5456	298	Virginia	-3.7276	528
Mississippi	-2.5886	257	Oklahoma	-3.7577	291
Maine	-2.6193	208	New Hampshire	-4.1011	399
Illinois	-2.6294	816	Iowa	-4.1603	249
Nebraska	-2.6339	324	New York	-4.4226	2835
Kansas	-2.6541	328	West Virginia	-4.8056	285
Kentucky	-2.7774	469	Minnesota	-4.8423	372
Colorado	-2.8109	363	Pennsylvania	-4.8700	873
Tennessee	-2.8554	397	Rhode Island	-5.0661	488
New Mexico	-2.9178	518	Wisconsin	-5.2446	279
Wyoming	-2.9401	319	New Jersey	-5.2594	598
North Dakota	-2.9789	331	Connecticut	-5.6912	242
California	-3.2206	2849	Massachusetts	-6.3191	761

Table 5: **Susceptibility Scores Estimated by Our Computational Model and Number of Sampled Users per U.S. State**. Due to insufficient data points, we only consider 48 contiguous states within the U.S.