

The Morbid Realities of Social Media: An Investigation into the Narratives Shared by the Deceased Victims of COVID-19

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Abstract

Social media platforms have had considerable impact on the real world especially during the Covid-19 pandemic. Problematic narratives related to Covid-19 might have caused significant impact on the population specifically due to its association with dangerous beliefs such as anti-vaccination and Covid denial. In this work, we study a unique dataset of Facebook posts by users who shared and believed in such narratives before succumbing to Covid-19 often resulting in death. We aim to characterize the dominant themes and sources present in the victim's posts along with identifying the role of the platform in handling deadly narratives. Our analysis reveals the overwhelming politicization of Covid-19 through the prevalence of anti-government themes propagated by right-wing political and media ecosystem. Furthermore, we highlight the efforts of Facebook's implementation of soft moderation actions intended to warn users of misinformation. Results from this study bring insights into the responsibility of political elites in shaping public discourse and the platform's role in dampening the reach of harmful narratives.

1 Introduction

The influence of social media in shaping our perception of sociopolitical realities is undeniable. It has long been understood and celebrated that their algorithms facilitate the democratization of content — enabling the amplification of otherwise unheard voices. In recent times, however, this has led to the amplification of problematic and harmful misinformation (Amarasingam and Argentino 2020; Fisher, Cox, and Hermann 2016). Indeed, recent findings show that their algorithms have been the target of effective, intentional, and inorganic manipulation efforts to promote a variety of conspiracy theories, erode trust in institutions, and generally sow political disharmony (Ryan 2022). As will be demonstrated in this paper, the consequences of such manipulation, unfortunately, transcend the virtual world and impact real people.

The abundance of misinformation was once again observed in the context of the Covid-19 pandemic where anti-establishment, anti-vaccination, and anti-science conspiracy theories were rampant (Nations 2020). In fact, in 2020, the

World Health Organization declared the abundance of information surrounding the Covid-19 pandemic, including misinformation and news from untrustworthy sources observed in digital media, as an *infodemic*. An infodemic is defined as false or misleading information that can cause confusion and risk-taking behaviors with adverse effects to health (Inf 2020). Although the exact harms of this infodemic are not measurable, it is noteworthy that: (1) the United States alone lost more than 1.05M individuals to the pandemic of whom nearly 100K were unvaccinated (Johnson 2022)¹; and (2) there have been many anecdotal reports linking these (likely preventable) deaths to the digital infodemic (Maloy and DeVynck 2021; Brummell 2022).

Prior work has largely sought to characterize the types and prevalence of various types of Covid-19 narratives on different platforms or to understand the effectiveness of platform moderation strategies at mitigating their harms. What is lacking, however, is a systematic effort to characterize the real-world impacts of different types of narratives and the entities that were responsible for amplifying their real-world harms. Our work seeks to fill this gap. Addressing this gap in research is important for several reasons: First and most broadly, it provides a deeper understanding of on-line trust, influence, and manipulation. Second, it provides insights into the specific epistemes that underlie problematic narratives that are capable of manipulation of beliefs or proves useful in the rationalization of already conceived beliefs. Finally, such a characterization might help platforms, influencers, regulators, and citizens better mitigate the harms from future infodemics.

Our contributions. *In this paper, we aim to characterize the problematic narratives that were present on the social media profiles of the deceased victims of Covid-19.* In other words, we analyze the Covid-19 narratives related to anti-vaccination and covid-denial themes by a large sample of the population who then succumbed were to Covid-19. The goals of this analysis is threefold: (1) to shed light into the narrative themes that were espoused and amplified by the eventual victims of the infodemic, (2) to identify the sources

¹For clarity: This includes individuals who succumbed to Covid-19 prior to the vaccine. According to the CDC, unvaccinated individuals are upto 53× more likely to succumb to Covid-19 (Johnson 2022).

(*elites* and domains) responsible for creating and propagating the associated problematic narrative themes, and (3) to identify the role of platforms in amplifying these deadly narratives. We expand on each of these below.

Covid-19 narrative themes (§3). We use a custom word-embedding to cluster textually and semantically similar posts. Next, we use random samples of posts from each cluster to manually label the narrative theme associated with the cluster. In our analysis, we focus specifically on measuring the prevalence of various themes and characterizing how Covid-19 victims navigated between these themes. Measuring the prevalence of each theme allows us to better understand the epistemes present in the infodemic that were used to: (1) manipulate victims’ beliefs about the pandemic or (2) help rationalize their pre-existing beliefs about the pandemic. Analyzing the patterns of victims’ navigation between themes helps us understand how a user might have adopted or propagated their harmful beliefs. Our results show strong evidence of the harms of the politicization of the pandemic with 67% of all victims sharing anti-government themed narratives (vs. 25% anti-vaccination, 27% anti-science).

Sources of problematic Covid-19 narratives (§4). Victims often share posts from prominent public figures or link to content in domains outside the platform. When this occurs, we refer to the public figure or the external domain as the ‘source’. In our analysis, we focus on characterizing the sources of problematic narratives observed in our dataset. We use public data sources to: (1) group public figures by their occupation and political stance and (2) group external domains by their bias and credibility. We then measure their prevalence and prominence in our dataset, and identify the narrative themes they propagate. This characterization allows us to identify the entities responsible for amplifying specific narrative themes. Our results once again emphasize the harms of politicization of the pandemic. Specifically, we see that the right-wing political and media ecosystem were the largest amplifiers of problematic narratives shared by the Covid-19 victims in our dataset.

The role of platforms (§5). Facebook, along with other social media platforms, announced the application of soft moderation (e.g., warning labels) on Covid-19 related posts and misinformation. In our analysis, we measured the completeness and consistency of platforms’ application of ‘soft moderation’ labels on victims’ misinformation posts. We then breakdown this analysis by sources and narrative theme to identify specific gaps in the application of these moderation interventions. Our results show that Facebook only applied soft moderation on 6% of all the posts. However, we find that the application of these interventions is consistent — i.e., posts with similar narrative themes are equally likely to obtain the same intervention. We find that verified users have a marginally higher likelihood of being the target of an intervention than non-verified users.

Taken all together, our analysis points to two key associations with the harms caused by the infodemic: the politicization of Covid-19 by the political elite and platforms’ failure

to effectively enforce interventions on Covid-19 misinformation and problematic narratives.

Caveat. It is important to note that we cannot and do not conclude that specific narrative themes (or entities) were causally responsible for the real-world harm inflicted on the victims. Rather, we claim that these narrative themes (or entities) were either (1) causally responsible for the victims’ harmful beliefs, or (2) used by victims to support or rationalize their already harmful beliefs. Put another way, our observational study can only yield correlated relationships (not causal relationships).

2 Data Collection

We perform our study on crowd-sourced collections of case studies of misinformed victims of Covid-19 posted online. These case studies contain posts of Facebook users, who openly declared their anti-vaccination, anti-mask, and anti-science beliefs online before succumbing to Covid-19 themselves. These posts present an opportunity to closely study the topics, sources, and the reactions of the platform that were associated with the beliefs that caused real-world harm. We source these collections from two sources: *r/HermanCainAward* and the website www.sorryantivaxxer.com. Both of these sources were designed for users to share stories about people who have made public declaration of their anti-vaccination, anti-mask or Covid-hoax beliefs followed by contracting Covid-19, such as the political figure Herman Cain, the namesake of the subreddit *r/HermanCainAward*. Therefore, they offer a unique and rare insight into problematic Covid-19 narratives including misinformation and propaganda posts associated with real-world victims of Covid-19. In our work, we define problematic narratives as an umbrella term encapsulating beliefs, opinions, satire, propaganda, and misinformation (Molina et al. 2021) that involve anti-vaccination, anti-mask or covid-denial narratives. We use the term ‘problematic’ to refer to the fact that these beliefs have been associated with real-world harm. It should be noted that these communities have been the subject of significant controversy due to their initial focus on schadenfreude. However, following public criticism and moderator actions, they have aligned their goals towards education of the harms of problematic Covid-19 narratives. We discuss our ethical considerations related to the use of these datasets in §7.

Datasets. We used the Reddit PRAW API ² to gather all submissions made to *r/HermanCainAward* between 08/21 and 02/22. Each submission contains a collection of images associated with a single victim of Covid-19 and each image is a curated screenshot showing evidence of the victim’s belief in problematic Covid-19 narratives. In total, we gathered 1.7K unique submissions containing 17.5K curated screenshots from Reddit. We used a cURL-based crawler to scrape all ‘stories’ published on the sorryantivaxxer.com website. Each story contains a time-ordered collection of Facebook screenshots showing evidence of the victim’s belief in problematic Covid-19 narratives. From sorryantivaxxer.com

²<https://praw.readthedocs.io>

axxer.com, we gathered 281 unique stories and extracted 3.2K curated screenshots associated with them. In total, our collection included 1.97K unique victims and 20.8K screenshots associated with their problematic Covid-19 related beliefs. We then used an Optical Character Recognition (OCR) tool (EasyOCR) to recognize and extract all text contained within the image. We conducted our analysis on this dataset of users, screenshots, and texts.

3 Problematic Covid-19 Narratives

Overview. In this section, we focus on: §3.1 identifying the themes of Covid-19 narratives seen in our dataset and uncovering how victims progressed through these themes; and §3.2 the entities and sentiments referenced in Covid-19 narratives.

3.1 Covid-19 Narrative Themes

We seek to answer the question: *What are the themes associated with the problematic Covid-19 narratives posted by victims, and how do they chronologically progress through these themes?* At a high-level, we use clustering based on semantic similarity in conjunction with manual cluster labeling to identify problematic narrative themes and harness the chronological ordering of screenshots associated with each victim to identify common theme progression patterns.

Methods. We now detail our methodologies for identifying themes and uncovering common progression patterns.

Identifying narrative themes. We assign themes to narrative using the following three steps.

- *Building a custom word embedding.* We begin by constructing a custom word embedding over the text extracted from all 20.8K screenshots in our dataset. We create this custom embedding using FastText (Wu and Manber 1992) for two key reasons: First, the vocabulary associated with Covid-19 narrative is unique and not captured in off-the-shelf embeddings. Second, we wish to preserve semantic and textual similarity between words. Maintaining semantic similarity means that words with lower distance between them in the word embedding are more semantically similar than those further away from each other. Maintaining textual similarity means that words with lower distance between them are more syntactically similar than words further away from each other — simply put, *similarly* (mis)spelled words are closer together than those that are not. This latter requirement is especially important in our process because our reliance on OCR to extract text from screenshots may result in the creation of text spelling errors. We use FastText specifically because it achieves both requirements.
- *Keyword-based post clustering.* Next, we generate TF-IDF vectors from the text associated with each post (using all 20.8K posts as the document corpus). These vectors provide a measure of importance (i.e., *weight*) to each word in the post. We use these weights to compute the weighted mean coordinates of the post in our custom embedding. For example, consider a post S , let $E(w)$ represent the coordinates associated with the word

‘ w ’ in the custom embedding, and $T(w)$ represent the TF-IDF weight associated with the word w in S . Then, we compute $\frac{\sum_{w \in S} E(w) \times T(w)}{|S|}$ as the weighted mean coordinates of S . This weighting allows us to place more emphasis on the words determined to be more important to a given post. We then use simple k-means clustering to cluster the weighted mean coordinates of all 20.8K posts in our dataset. We use cluster coherence metrics and the elbow method in conjunction with manual validation to settle on $k = 44$ for our dataset.

- *Manual label assignment.* Finally, we randomly sample 12 posts from each cluster and use an expert to determine the theme of the narrative contained in each cluster. We then apply this label (i.e., theme) to all posts within the cluster.

Measuring theme progression. In order to understand the relationships between themes in our dataset, we convert our data into a directed graph representation. In this directed graph, we represent each theme as a node and use directed edges to denote the chronological ordering of themes observed for each user in our dataset. Thus, the weight on the directed edge from one node (n_1) to another (n_2) represents the number of users who posted narrative of theme n_1 and immediately followed it by theme n_2 . Next, to group topics that are more connected with each other, we perform the Louvain method for community detection (De Meo et al. 2011). This identifies cliques with densely connected nodes. In the context of our analysis, these cliques represent narrative themes that are contiguous and compatible with each other.

Results. In total, we identified 14 unique themes of narratives ranging from anti-government to alternative medication. Disturbingly, 82% of all users made posts regarding their own death and over 30% made statements of regret or pleas for help. A full list of the themes and their prevalence across victims and posts is shown in Table 1. Our analysis shows that political (anti-government and anti-democrat) themes which suggested a lack of trust in the (state or federal) government or the democratic party occurred for significantly more victims (and posts) than anti-science, anti-vaccination, conspiracy, or alternative medication themes. From our chronological analysis, we find that over 38% of all posts were made after contracting Covid-19.

From our theme progression analysis, we observe several common patterns in user engagement of Covid-19 narratives. First, we find that anti-masks/mandates and pro-freedom themes were most commonly observed as a gateway to other problematic themes. This is likely capturing the victims’ initial reactions to Covid-19 lockdowns and mandates. Conversely, the most frequently observed terminal narrative stages included anti-government and anti-vaccination posts. The themes found to co-occur least with other themes were religion and alternative solutions/medications. Second, nearly 63% of all victims in our dataset appeared to follow a similar progression through narrative themes. These are illustrated in Figure 1. We find the most common cohort to include multiple anti-government themed

Topic	% of victims	# posts
<i>Anti-Government</i>	67	3040
<i>Anti-Science</i>	27	750
<i>Anti-Vaccination</i>	25	727
<i>Anti-Democrat</i>	21	544
<i>Masks</i>	21	564
<i>Religion</i>	19	532
<i>Alternative Solutions</i>	17	439
<i>Mandates</i>	15	371
<i>Immigration</i>	9	209
<i>General Covid</i>	8	170
<i>Pro-Freedom</i>	6	134
<i>Conspiracy</i>	5	105
<i>Quarantine</i>	1	17
<i>Death</i>	82	2725
<i>Regret</i>	31	1174
<i>Asking for Help</i>	30	883

Table 1: Prevalence of themes in posts and victims. The bottom three rows denote topics identifying contraction of Covid-19 and its consequences followed by their prevalence.

posts followed by posts on masks and mandates. Alternatively, we also observe users sharing a sequence of posts initiating with anti-Democrat posts and then generalizing to anti-government topics. In some cases, users tend to post anti-government posts followed by anti-vaccination posts as well suggesting some form of influence between anti-government and anti-vaccination beliefs. Finally, the biggest cohort without any anti-government themes included intellectual narratives starting from anti-science posts to anti-vaccination and finally alternative solutions. Users posting alternative solutions were also found to be the least likely to share Covid-19 posts with regret.

3.2 Entities in Covid-19 Narratives

In this section, we seek to answer the question *What are the entities associated with problematic Covid-19 narratives posted by victims, and what are the sentiments towards these entities?* Using part-of-speech tagging and sentiment analysis, we seek to identify the prominent entities present in our dataset, measure their distribution in the identified Covid-19 narrative themes and measure the sentiments associated with them.

Methods. We now detail our methodologies for identifying entities and measuring their associated sentiment.

Identifying entities. We identify common entities present in our dataset by identifying and collecting all the nouns from our dataset. This is done by first preprocessing and tokeniz-

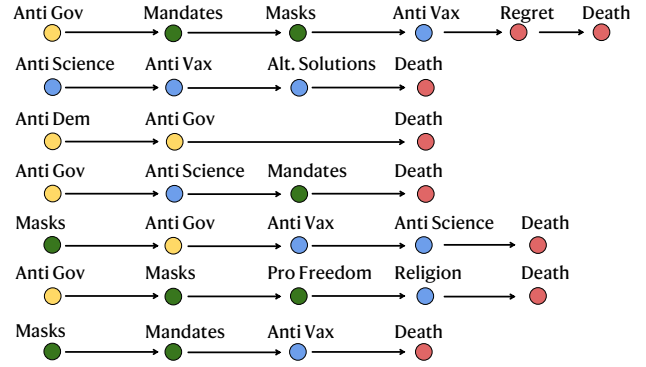


Figure 1: Representation of the most common progressions through narratives along with the percentage of users with similar progression. Colors of the nodes represent the cluster each topic belongs to based on the Louvian community analysis.

ing the extracted text from all the screenshots present in our dataset and then performing a part-of-speech tagging algorithm. This tags each word with a word category such as noun, verb, and adjectives. Since we seek to identify the entities in our dataset, we collect all the words tagged as noun and discard others, we consider the list of nouns as entities. To filter out uncommon entities, we remove all entities that appear in less than 10% of the posts in our dataset. Next, we perform manual filtering on this list to group together entities with the same meanings such as *vaccinations*, *vaccines*, and *shots*. This totals to 243 entities that have appeared in 10% of the posts or more.

Entity sentiment analysis. Next, we measure the sentiment towards these entities in the user’s posts. To this end, we utilize Google’s Cloud Natural Language API to perform entity sentiment analysis. The API yields a sentiment score between -1 and +1 representing the overall emotion towards the particular entity and a magnitude score representing the strength of the emotion. We set the range for clearly positive sentiment at greater than 0.5 and clearly negative sentiment at less than -0.5. We process all the extracted text from screenshots with at least one of the identified entity present and calculate the sentiment towards the entity. Finally, for our purposes, we compute the average sentiment towards each entity from all of its mentions.

Results. We identify most common entities to include *covid*, *vaccine*, *virus*, *masks*, *news*, *government*, *shot*, and *news* with their mentions making up total of 32% of all entity mentions. From our entity sentiment analysis, we observe religious entities such as *Jesus*, *amen*, *lord*, and *church* to have the highest percentage of positive sentiment (82% - 79%). This can be explained by the presence of non- followed by entities such as *Ivermectin*, *truth*, and *country*. The entities with the highest percentage of negative mentions were *mandates*, *businesses*, *china*, *government*, *masks*, *president*, *Biden*, *vaccines*, and *Fauci*. Distributing the entities across Covid-19 narrative themes identified in §3.1, we observe the entities to match the themes such as government

related entities being the most common in anti-government posts with high values for negative sentiments.

3.3 Takeaways

In studying the content of the posts, we identify a significant dominance of government related posts which suggests some level of politicization of COVID-19 in our dataset. Further inquiry in the progression of the narratives by users suggest narratives to be centered more around reactive narratives to resist recommendations, mandates and policies by the authorities as we observe in our cohort analysis. The cohort analysis further confirms the dominance of political topics in the dataset and the slight separation between conspiratorial topics and mainstream political topics.

4 Sources of Problematic Narratives

In this section, we focus on uncovering the role of public figures (§4.1) and external domains (§4.2) in the origination and amplification of narrative themes.

4.1 Public Figures as Sources of Narratives

Public figures on social media platforms have a significantly different role in an information cascade. Prior research highlights the importance of elites and thought leaders to generate and propagate information in cascades. As explored by Zhang et al. (Zhang et al. 2014), users are more likely to consider verified public figures to be more credible and trustworthy. Therefore, we seek to answer the question: *How do public figures interact with different narratives and their progression?* At a high-level, we answer this question by extracting all posts made by Facebook ‘verified users’ that are shared by victims in our dataset. We then obtain communities of verified users that frequently co-occur in our dataset. We then analyze the themes of narratives from verified users by the user’s occupation and political leaning (obtained from external sources).

Methods. We now outline our methods for extracting posts of verified users shared by victims, obtaining occupation and political leanings of verified users, and identifying communities of verified users.

Extracting posts of verified users shared by victims. To identify and measure the involvement of public figures in the narratives we first need to identify whether a public figure is present in the screenshot of the post. In this section, we outline the methods used to identify a public figures presence in a post and collect their defining characteristics such as their occupation and partisanship. First, to identify whether a public figure is present in a screenshot of a post we use Facebook’s verified badge label as an identifier. Facebook, along with other platforms, places a verified badge next to the names of verified public figures in their posts. The intent of the verified badge is to ensure the post is authored by an account which is verified to be actually controlled by the public figure. Since Facebook assigns the verified badges only to public figures, we use the badges as a proxy for identifying public figures. To identify whether a verified badge is present in a screenshot, we use SIFT template matching algorithm. SIFT template matching algorithm is a computer

vision technique to identify whether a template, which in our case is the verified badge, is present in an image. We perform the SIFT template matching algorithm on all the screenshots in our collection and curate a set of screenshots that contain at least one verified badge. Next, using a combination of image analysis, to locate the text next to the verified badge, and OCR, to extract the text, we extract the name of the public figures present in the screenshot.

Obtaining occupation and political leaning of verified users. To assign attributes to each of the public figure, we search for their name on Wikipedia using the Wikipedia API. For each public figure, we find their occupation and partisanship from their Wikipedia page summary manually. The occupation of a public figure allows us to explore their credibility and influence over their audience while their partisanship, if any, enables us to identify partisan sources in Covid-19 narrative.

Identifying communities of verified users. Finally, to measure the involvement of public figures in the progression of users narratives and beliefs, we construct an undirected graph of the posts with public figures to measure a user’s involvement with them and their compatibility with each other. We connect the public figures, represented as nodes, in the graph with edges representing the volume of users that have shared both of the public figures posts. Using this graph, we extract ‘communities’ of public figures that were shared by a cohort of users. Similar to our identification of theme progressions, this is done using the Louvain community identification algorithm (De Meo et al. 2011).

Results. In our collection of 20.8K unique posts, we identified 200 unique public figures whose content was shared by our victims. In total, these accounted for approximately 2.5% of all our victims’ posts. The most frequently shared figures included right-wing political commentators Tucker Carlson, Candace Owens, Tomi Lahren, and Ben Shapiro who accounted for at least 20% of all shared posts. Breaking down these figures by their derived occupations and political leanings, we observe an obvious pattern (shown in Table 2) — political elites (commentators and politicians) on the right-wing were most likely to be the source of the posts shared by our victims.

Next, studying the involvement of public figures in the identified narrative themes and progressions, we observe that posts with a public figure were more likely to engage with anti-democrat and anti-government themes compared to posts authored by the victims themselves (i.e., non-shared posts). The high frequency of these political themes from verified users can be explained by the presence of high number of right-wing political elites. This is shown in Table 3. Looking simply at the types of posts made by verified users, we found that posts including a public figure had significantly more focus on anti-democratic and anti-immigration (e.g., suggesting Covid-19 deaths were due to an immigration crisis) themes compared to masks, conspiratorial narratives, and anti-science claims. These results suggest that, at large, the political elites were not very likely to peddle conspiracy or anti-science theories. Instead, they focused on politicizing the pandemic and challenged perceptions of

Category	Most frequent figure	Left	Neutral	Right	Total Unique
Political Commentator	Tucker Carlson	1	1	195	42
Politician	Ted Cruz	4	0	100	52
News Network	Fox News	12	16	65	45
Advocacy Group	Turning Point USA	1	0	55	22
Celebrity	Gina Carano	0	39	1	17
Health Agency	CDC	0	9	0	6

Table 2: Number of posts including a public figure distributed by occupation and partisanship of the public figures in our dataset.

trust in the government and its institutions. Further, highlighting the power of elites and public figures, we observed that victims who shared posts from public political figures showed a 22% (statistically significant) higher likelihood of also authoring similar posts themselves (when compared to users who did not share posts from political figures).

Our analysis using the undirected graph of the public figures show that it is common for users to share mainstream public figures such as the overlap between mainstream right-wing political commentators (Tucker Carlson, Ben Shapiro, and Candace Owens) right-wing politicians, (Ted Cruz, Donald Trump Jr.) and right-wing advocacy groups (PragerU, Turning Point USA) were significant enough for the creation of a community. This shows that users who post mainstream right-wing personalities are more likely to post or mention more mainstream right-wing personalities. Other prominent cliques included groups of celebrities, satirical websites such as BabylonBee, and advocacy groups. The formation of the right-wing mainstream clique highlights an interesting fact that their narrative themes are similar and compatible enough (largely centered around anti-government and political themes) to be shared by the same users. Finally, observing patterns around the progression of how content from verified users is shared by victims, we observe two large cliques of victims. One clique exclusively focused on sharing posts from different right-wing news networks and the other exclusively focused on sharing posts from different right-wing political commentators.

4.2 External Domains as Sources of Problematic Narratives

Similar to the public figures online, external domains have been studied to have a significant influence on the reach of an information cascade. Tanaka et al. (Tanaka, Sakamoto, and Matsuka 2012) show how the inclusion of an external domain in a tweet makes it twice as more likely to be retweeted suggesting that content with external domains are more likely to be shared and propagate further in a cascade. Therefore, we seek to answer the question: *How are external domains exploited for the propagation of different narrative themes?* We answer this question by identifying all posts shared by victims that include a link to an external domain. We then categorize these domains by their reputations and analyze their involvement in victims’ progression through narrative themes.

Methods. In order to analyze the involvement of external domains in a narrative theme, we first need to extract the external domains present in each screenshot in our dataset and assign meaningful attributes to the domains. First, to identify whether a screenshot of a post contains a URL, we take the text of the post and find any URL in the text using URL matching regular expressions. Following the identification and extractions of our URL, we isolate the domain part of the URL and discard the rest. Next, we identify the attributes of the domain which inform us about its reputation and authenticity using Media Bias/Fact Check (MBFC) (Huitsing 2018). We use MBFC to obtain the political bias and factual reporting frequency for each domain and correlate these with narrative themes and progressions. Finally, similar to our public figure analysis, we create a graph to explore the compatibility of external domains.

Results. In our dataset, we identify a total of 2.5K domains (925 unique domains). Notably, 49% of the victims in our dataset did not share a single link to an external domain — i.e., all their posts were from within Facebook. The most frequently observed domains were from video streaming platforms such as Youtube, Rumble, and Bitchute. News-related domains such as Fox News and The Epoch Times accounted for a total of 24% of the URL-containing posts. These formed the basis of our MBFC attribute analysis. We observed that these shared external news domains contained a significant amount of bias and narrative. In our data, only 4% of the domains had no bias, while 20% had center-left alignment, and 6% had center-right alignment. The remaining domains were right (40% of all domains) or far-right aligned (29% of all domains). In other words, exploring the domains being shared in our dataset, we observe a significant skew towards right and far-right sources. Furthermore, we observe a significantly positive correlation between the domain’s alignment with the right and lack of factual reporting. Contrasting our previous results related to public figures, as shown in Figure 2, conspiratorial and pseudo-science topics such as anti-vaccination, alternative solutions and anti-science topics were significantly more prevalent. This result suggests that external domains (often unmoderated) are more likely to be used as a source to spread non-factual (anti-vaccination, alternative solutions and anti-science) topics. In our analysis on whether there are any patterns of users progression through the domains, we observe a significant decrease in factual reporting and an increase in

Topics	Dist. of posts		% Dist. of posts by occupation (Right)			% Dist. of topics in each group		Avg. Effect
	Total	V	PC%	P%	NN%	V%	NV%	
<i>Anti-government</i>	3040	181	27	29	14	23	58	0.35*
<i>Anti-science</i>	750	9	22	22	0	6	3	-0.03*
<i>Anti-vaccination</i>	727	15	33	13	7	6	5	-0.01
<i>Masks</i>	564	3	33	33	0	5	1	-0.04*
<i>Anti-Democrat</i>	544	53	74	4	4	4	17	0.13*
<i>Religion</i>	532	4	25	25	25	4	0	-0.03*
<i>Alt Solutions</i>	439	8	12	0	12	4	3	-0.01
<i>Mandates</i>	371	7	29	29	0	3	2	-0.01
<i>Immigration</i>	209	9	33	33	11	2	3	0.01
<i>General-COVID</i>	170	2	0	0	0	1	1	-0.01
<i>Pro-Freedom</i>	134	0	0	0	0	0	0	0.00
<i>Conspiracy</i>	105	1	0	0	0	1	0	-0.01
<i>Quarantine</i>	17	0	0	0	0	0	0	0.00
<i>Asking for help</i>	883	2	0	0	0	7	1	-0.07*
<i>Regret</i>	1174	5	20	40	0	10	2	-0.08*
<i>Death</i>	2725	13	23	8	0	22	4	-0.18*

Table 3: Distribution of topics in posts by verified users along with the % distribution of users by each topic. The avg. effect column represents the increase in likelihood of a post being of that particular topic given a user is verified. V and NV denote verified and non-verified users, respectively. PC, P, and NN denote political commentators, politicians, and news networks, respectively. * indicates statistically significant average treatment effect ($p < .05$).

severity of bias towards the right as we progress through a user’s posts timeline. This suggests, that users might start with slightly factual and neutral sources and later progress to consume and spread less factual and more bias content.

4.3 Takeaways

Taken together, the results from this section underscore the prominent involvement of right-wing political commentators, politicians and news networks in the politicization of Covid-19 by their almost exclusive involvement in political themed narrative. Our dataset highlights the high percentage of users who had adopted and were sharing politicized narratives surrounding Covid-19 that reflected their harmful beliefs. Our analysis on the external domains also confirms the narrative, especially related to anti-vaccination beliefs, alternative solutions to Covid-19 and claims refuting the science of Covid-19, was exceedingly being sourced from biased and non-credible external domains which often contained blogs and videos from unregulated platforms.

5 Moderation of Misinformation

During the Covid-19 pandemic, in Feb. 2021, Facebook announced an expanded effort to improve moderation of

Covid-19 misinformation. Specifically targeted themes were related to anti-vaccination, conspiracy theory, and anti-science misinformation (Rosen 2020). These moderation efforts included outright removal of content or the application of ‘soft moderation’ warning labels on content. In this section, we focus on evaluating the completeness (§5.1) and consistency (§5.2) of this effort.

5.1 Completeness of Interventions

We now evaluate the fraction of misinformation posts in our dataset that received a soft moderation intervention. Next, we analyse the application of these interventions broken down by the misinformation theme to identify specific gaps in moderation.

Methods. We are unable to measure the posts deleted by Facebook, so we restrict ourselves to measuring the application of soft moderation interventions on misinformation posts shared by victims. The visible soft moderation interventions are limited to flagging the content with one of the following labels:

1. *False Information.* This flag means the information found in the post is categorically false. Facebook state’s content

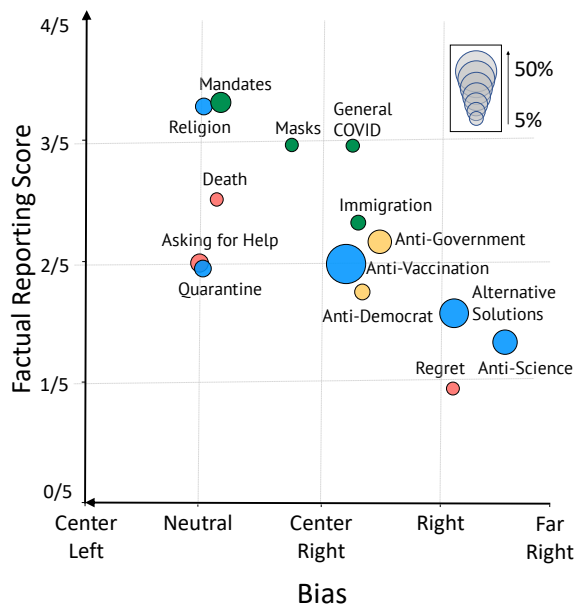


Figure 2: Percentage of posts with external domains in each topic category along with average bias and factual reporting score of the domains present. The size of the bubble is proportional to the percentage of posts with the topic containing an external domain.

flagged as false information experiences dramatic reduction in its distribution and strong warning labels.

2. *Partly False Information.* Content labeled with this flag include some factual inaccuracies. The interventions performed on content labeled partly false information are less severe compared to content labeled false information.
3. *Context Missing.* Posts labeled with this flag have the potential to mislead its readers without additional context. The interventions towards this type of content are minimal and are limited to a warning label stating that context is missing from the post.
4. *More Information Required.* Posts with this label are not identified as misleading or misinformation rather are provided with a redirect to information center to access more information regarding Covid-19. Posts labeled with this flag have mentions of vaccines and Covid-19 related topic.

To identify whether a screenshot contains a post that is flagged and extract which type of label has been flagged we perform template matching with text. Using the extracted text from each of the post we search for string templates created for each of the label above. Finally, we compute the distribution of each type of label for each misinformation theme and source.

Results. In our dataset, we found only 6% of the posts to be flagged by on the labels — suggesting out of the 20.8K problematic posts which included proclamation of beliefs, satire, and personal experience, Facebook’s moderation team con-

sidered only 1.2K posts to contain sensitive content to illicit a label. This small percentage of posts labeled by Facebook suggests how the majority of the posts only contained non-misinformation related problematic content that could not have been moderated by Facebook. The categories of problematic content outside of misinformation highlight a unique challenge for modern social media platforms. Where problematic and in this case dangerous beliefs absolutely do not call for any for of intervention therefore lifting the burden from the platform to the creators and readers of such content specifically in cases where the creators are trusted sources of information. In our analysis, we observe public figures to be primarily focused on non-misinformation related problematic narratives. Out of these labeled posts, 145 were labeled as false information, 133 were labeled missing context, 114 were labeled partly false information and 889 were labeled to redirect the user to more information. In Figure 3 we show the distribution of the labels in each class. Here we see the ‘False Information’ label being primarily distributed among anti-vaccination, anti-government, and anti-science — suggesting these themes are more likely to be screened by Facebook fact checkers. Switching dimensions, we see that the anti-government and anti-vaccination themes are also the most frequent subjects of any type of soft moderation. Of concern, however, is that alternative solutions and anti-science posts are often not the subject of any interventions.

The most common entities present in posts labeled as ‘False Information’ or ‘Partly False Information’ are *vaccines*, *media*, *science*, *masks*, *CDC*, and *virus* with these entities accounting for 53% of all the labels. Studying the distribution of misinformation labels over verified users, we do not observe any significant presence and find only 3 unique posts by right-aligned political commentators to ever receive a ‘False Information’ label. However, we do observe a significant increase of 6% likelihood of experiencing a label ‘redirecting to the information center’ for posts from verified users. Next, we observe containing an external domain in a post significantly increases the likelihood of being labeled with a misinformation label. In total, we observe, out of the 2.5K URLs mentioned, 38 containing ‘False Information’ labels, 34 containing ‘Missing Context’ labels and 34 containing ‘Partly False Information’ labels accounting for 28% of all misinformation labels. The distribution of misinformation on external domains further increases as factual reporting decreases and the bias skews towards far right with the far-right URL’s having the highest percentage of misinformation labels (10%) compared to other alignments.

Results. In our dataset, we found only 6% of the posts to be flagged by one of the labels — suggesting that Facebook’s efforts at curbing Covid-19 misinformation was far from adequate or complete. Out of these labeled posts, 145 were labeled as false information, 133 were labeled missing context, 114 were labeled partly false information and 889 were labeled to redirect the user to more information. In Figure 3 we show the distribution of the labels in each class. Here we see the ‘False Information’ label being primarily distributed among anti-vaccination, anti-government,

and anti-science — suggesting these themes are more likely to be screened by Facebook fact checkers. Switching dimensions, we see that the anti-government and anti-vaccination themes are also the most frequent subjects of any type of soft moderation. Of concern, however, is that alternative solutions and anti-science posts are often not the subject of any interventions.

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5.2 Consistency of Interventions

Consistent content moderation is central for effective moderation. In this section, we use our limited dataset whether Facebook’s interventions were consistent.

Methods. To identify whether Facebook’s soft moderation were consistent across posts with the same content in our dataset, we use a combination of text analysis and manual validation. By identifying all the posts with misinformation labels in our dataset, we search for posts with similar keywords in our dataset. Following this collection we validate, using the misinformation label string templates and manual validation, the consistency of the application of Facebook misinformation label.

Results. We identify 42 posts labeled false or misleading while also having nearly identical textual/semantic content to other posts in our dataset. We find the labeling of misinformation to be consistently applied in all posts sharing highly similar content. One key difference between the posts, however, was the design of the misinformation label. While some posts had a superimposed label partially obstructing the content of the post, others had no obstruction and had the label present at the bottom of the post. This finding suggests the presence of a moderation tool to identify and flag posts similar to previously moderated posts.

5.3 Takeaways

Our analysis, albeit on a small dataset, suggests that Facebook’s interventions are consistent but far from complete.

Specifically, these findings suggest that Facebook’s misinformation moderation efforts: (1) are most targeted towards very specific types of anti-vaccination and anti-government themes — largely ignoring others, (2) do not appear to hold public figures to a higher standard than regular users, (3) is adept at flagging content from problematic external domains, and (4) utilize a mechanism to flag posts similar to already moderated posts.

6 Related Works

Our work makes three key contributions operating on a unique dataset of posts made by Facebook users with harmful beliefs related to Covid-19. We identify and characterize the themes and sources these users engaged along with the reaction of Facebook in the form of soft moderation actions. In this section, we place our work among other studies performed on Covid-19 misinformation campaigns across different social media platforms.

Problematic narrative themes. Misinformation, propaganda and other problematic content has been a long-standing problem in the social media space and understanding the narratives and themes that drive problematic beliefs has become a key area of research. The Covid-19 narratives found on Twitter (Jiang et al. 2020; Havey 2020) give support to our results from §3.1 where we observe misinformed Facebook users to have politicized the Covid-19 discussion. The authors, in studying the discussion related to Covid-19 on Twitter, find political narratives to be the most prominent theme and additionally for conservative users to be more engaged in conspiratorial and political narratives. The authors argue the politicization of Covid-19 discussion to be a key reason for the dire consequences stemming from being distracting from actual health and pandemic related discussion. Finally, in their work identifying the information being propagated by bots on Twitter related to Covid-19 (Ferrara 2020), the author finds bots promoting already present pro-freedom alt-right ideologies and spreading conspiratorial narratives. We find the narratives the bots, motivated by an agenda to spread misinformation, spread and promoted most frequently on Twitter matched with the Covid-19 themes identified and propagated by questionable external domains in our analysis of Facebook posts.

Misinformation sources. Research in understanding the sources of information has been a key area of understanding how misinformation propagates online. The role elite users and external domains play in establishing trust, credibility and authority in information cascades has been well studied across different platforms. Specifically, related to misinformation on Covid-19, research done by Muric et al. show the prominent role low credibility sources play in the spread of Covid misinformation (Muric et al. 2021). Studying a dataset of anti-vaccine stance posts from Twitter, Muric et al. observe the most common links to be from low credibility media sources and being shared by right-leaning accounts. This observation is supported by our results from Figure 2 where we observe anti-vaccination claims to be accompanied by external domains of low credibility and having a right-leaning bias. A study on general early Covid-

Dist. of content labels for each narrative theme.	Alt Solutions	Anti Democrat	Anti Gov	Anti Vax	Anti Abortion	Anti Science	Asking for help	Conspiracy	Death	General Covid	Immigration	Mandates	Masks	Pro Freedom	Quarantine	Regret	Religion
False Information	6	3	29	17	0	17	3	0	14	3	0	6	3	0	0	1	3
Missing Context	4	0	14	33	2	27	1	0	9	0	0	3	2	4	0	0	0
Partly False Info	12	2	24	18	0	11	1	1	5	1	2	13	3	0	0	3	0
Visit Info Center	4	5	32	22	5	11	4	1	28	6	10	16	8	12	0	8	14
None	2	2	15	4	0	4	6	0	20	1	2	3	5	5	0	62	70

Figure 3: Percentage of misinformation labels present in each topic.

19 narratives on Twitter by Singh et al., however, show the significantly overwhelming presence of high quality media sources compared to low quality sources. Presence of high quality media sources in early general narratives of Covid-19 compared to high presence of low quality sources found in our dataset specifically in anti-vaccination narratives of Covid-19 confirms our observation of the role of external domains in the spread of harmful beliefs on Covid-19 in misinformed users. Exploring the role of verified users on Twitter, Andrews et al. observe the power official accounts have in spreading and correcting associated rumors (Andrews et al. 2016). Furthermore, Yang et al. show how verified users on Facebook play a much significant role in spreading lower credibility information compared to verified users on Twitter (Yang et al. 2021). These results highlight the inaction of verified users found in our dataset in correcting misinformation and spreading politically polarized narratives.

Platform interventions. Over the recent years, researchers have studied the effectiveness of content moderation on social media platforms that include removal of content and communities. Recently however, amidst the fears of fake news and misinformation, social media platforms have started performing soft moderation interventions to warn users about the accuracy of content. These soft moderation actions include warning labels, overlays, and tags warning the user about the misrepresentation or misinformation present in a post. Research into understanding how effective these soft moderation interventions have been in limiting the engagement and reach of misinformation highlights the efforts still required to ensure consistency, completeness and effectiveness. Mena et al., in their work (Mena 2020) study the effectiveness of Facebook’s soft moderation interventions on misinformation. They find that Facebook’s soft moderation interventions are effective in reducing the likelihood of a user sharing a post with a warning label. However, an empirical study by Zannettou finds Twitter’s warning labels to be not as effective especially for Republican users (Zannettou 2021). Additionally, they find Twitter’s soft moderation strategies to be inconsistent and often perceived

as acts of censorship. These results are further confirmed by Sharevski et al. in their 319 participant study to measure how users perceive Tweets with or without warning labels (Sharevski et al. 2022). Their analysis, focused on COVID-19 misinformation, show people to resist warning labels especially if the warning labels are not designed to cover the entire post. Additionally, their study highlights the strongest predictor of perception of the accuracy of a post to be the prior belief of a user rather than the presence of a warning labels. They argue that extended use and misuse of warning labels might backfire in misinformed users to completely ignore warning labels by perceiving the moderator as being biased.

7 Concluding Remarks

Limitations. Fundamentally, this work is a ‘best-effort’ observational study aimed at better understanding the role that the infodemic played in the large number of Covid-19 deaths amongst the unvaccinated. Consequently, there are three important limitations that influence our study and its findings.

Dataset limitations. Our reliance on crowd-sourced datasets, although necessary to overcome data gathering limitations placed by social media platforms (Facebook, in particular), introduce challenges to representativeness. More specifically, we cannot ensure that the dataset contains a complete record of all the misinformation shared by a victim. Since a victim’s posts were curated by other individuals for the purpose of cataloging in communities engaging in schadenfreude, it is possible that not all misinformation-related posts were recorded and a selection bias was introduced in the cataloging process (e.g., by selecting only the loudest anti-vaccination victims of Covid-19 for cataloging, or by selecting only specific types of posts from a victim). Despite these challenges, we argue that our investigation and findings are important because these curated datasets present a rare and unique opportunity to understand the characteristics of misinformation encountered by the misinformed victims of the Covid-19 pandemic. Further, the large number of

unique victims and individual curators in our datasets suggests that the general trends observed in our results must be representative of a large segment of the US population.

We can only uncover correlated relationships. Because our study is observational, there is little opportunity to derive any insight into causal relationships between misinformation themes (or entities) and the victim's beliefs/passing. This limits our conclusions to correlational relationships that suggest either causation (victim adopted a belief because of a post) or rationalization (victim made a post because it fit their beliefs). Additionally, our ability to run observational control-treatment analyses is limited due to Facebook's scraping limitations that prevent us from creating a meaningful control group. Despite these limitations, our study is still able to draw conclusions regarding the epistemes of misinformation (and their sources) that were most likely to resonate with the eventual victims of Covid-19.

Text extraction may introduce errors. Finally, our analysis required text extraction from screenshots – an already noisy task further complicated by the cropping styles used by contributors, the presence of mixed-media posts (e.g., an image of text of varying fonts inside a screenshot), and the importance of extracting sources of shared posts. At each step in our extraction pipeline, we conducted manual validation of random samples to ensure high fidelity text extraction. Despite this effort, unfortunately, we cannot guarantee correctness over the entire dataset.

Ethical considerations. Conducting this study was a challenging task, largely owing to the questionable ethics of the dataset being studied and the communities that curated them. In fact, there has been much media attention and criticism showered on these communities for the unempathetic discourse surrounding the victims of Covid-19 — even spilling over to public conflicts between the moderators of the communities (Judkis 2022). We undertook this work from the perspective that the victims cataloged by these communities were ultimately failed by our political climate, leaders, and the platforms they relied on. This paper is meant to highlight these failures so they may not repeat. With regards to operational ethical considerations, our study did not scrape posts from non-public domains and did not violate the scraping limitations set by any platform/website. Whenever available, we relied on an official API for data gathering and analysis. Finally, our dataset of screenshot of posts does not include any personally identifiable information. The names and pictures of the posters (unless the poster is a public figure) were made illegible by the curators.

Conclusions. In our study, we investigate a sample of problematic narratives shared by the victims of Covid-19 online. Our analyses suggest two key associations with the harms caused by the infodemic: the politicization of Covid-19 by the political class and limited moderation by online platforms. More specifically, our findings show that the anti-government theme of narratives propagated primarily by the right-wing political and media ecosystem was significantly more prevalent than anti-science, anti-vaccination, and Covid-denial themes amongst the victims of Covid-19

cataloged in our datasets. This result highlights the responsibility held by the political elites (and also the platforms that promote their voices) towards the masses and is complementary to the long line of work in the political sciences focused on showcasing the power and authority of political elites in shaping public opinion in times of crisis. (Hutcheson et al. 2004; Jennings 1992; Bachrach 2017). Our findings from studying the soft moderation techniques of Facebook can inform the discussion around the role of platforms in propagating problematic content besides misinformation. The non-misinformation problematic narratives (including narratives sharing personal experiences and opinions contradicting scientific studies) can not be categorized as misinformation and moderated against yet can still have real world consequences specially with the involvement of trusted public figures. It is paramount that platforms (or their regulators) recognize their sociopolitical influence and deliberate over the design of their platforms/algorithms to dampen or at least not magnify the reach of harmful narratives.

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