A Psycho-linguistic Analysis of BitChute
A Metadata Supplement to The MeLa BitChute Dataset

Benjamin D. Horne
School of Information Sciences, University of Tennessee Knoxville, Knoxville, TN, USA
bhorne6@utk.edu

Abstract
In order to better support researchers, journalist, and practitioners in their use of the MeLa-BitChute dataset for exploration and investigative reporting, we provide new psycho-linguistic metadata for the videos, comments, and channels in the dataset using LIWC22. This paper describes that metadata and methods to filter the data using the metadata. In addition, we provide basic analysis and comparison of the language on BitChute to other social media platforms. The MeLa-BitChute dataset and LIWC metadata described in this paper can be found at: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/KRD1VS.

1 Introduction
The alt-tech ecosystem, a set social media platforms that exist in answer to perceived risks of censorship from large social media platforms, has created a digital infrastructure for fringe groups, particularly on the far-right (Jasser et al. 2021; Donovan, Lewis, and Friedberg 2019; Wilson and Starbird 2021). Platforms in this ecosystem have provided many technological affordances to these groups, such as low content moderation, mechanisms to grow engaged audiences, and sometimes even funding structures for content production (Jasser et al. 2021; Trujillo et al. 2020).

Due to these affordances, a primary concern with the continued growth of alt-tech platforms is, for lack of a better term, the offline harms that are facilitated or incited by online activities and extremist movements on those platforms (Munn 2021). For example, it has been argued that violent events such as the 2016 Comet Ping Pong pizzeria gunman (Pizzagate), the 2017 Unite the Right rally in Charlottesville, and the 2021 U.S. Capitol attack have each had online components, ranging from organization, coordination, and inspiration. Although, the effect of social media on ideology, events, and actions is widely debated (Guess et al. 2018; Flaxman, Goel, and Rao 2016; Althoff, Jindal, and Leskovec 2017; Rice et al. 2022), gaining a better understanding of what types of calls to violence exist online and the dynamics involved in potentially violent movements is still salient.

Work by qualitative, ethnographic researchers and investigative journalists is critical in gaining this understanding. Often, in quantitative, big data research, we focus on the the elite, highly-productive, and highly-engaged with content producers in a space, sometimes missing the smaller players, who may still generate consequential harms both online and offline. Yet, filtering large datasets to smaller datasets suitable for qualitative work is time-consuming and can be a barrier-to-entry to studying niche, yet consequential, behaviors on large social platforms.

Released in early 2022, the MeLa-BitChute dataset (Trujillo et al. 2022) provides a large, near-complete sample of data from 3M+ videos, 11M+ comments, and 61K channels on one such alt-tech platform, BitChute. Given the structure of the dataset, it is suitable for large-scale studies of the platform out-of-the-box, but requires some additional effort to perform small-scale, qualitative studies of the platform. To better facilitate and support qualitative studies and explorations of the platform, we provide a psycho-linguistic metadata set over the MeLa-BitChute dataset using LIWC-22. In this short paper, we describe this metadata set, describe several use cases, and provide practical guidance on using it.

Both the original MeLa-BitChute dataset and the metadata described in this paper can be found in the following repository: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/KRD1VS. The paper documenting the original dataset collection and structure can be found in (Trujillo et al. 2022).

2 Linguistic Inquiry and Word Count
Linguistic Inquiry and Word Count (LIWC) is a theory-driven, dictionary-based method to measure various psychological states from open-text, dating back to 1993 (Francis and Booth 1993), conceptually stemming from work in Psychology from 1942 (Allport 1942). The method has been improved upon over time, with updates in 2001 (Pennebaker, Francis, and Booth 2001), 2007 (Pennebaker, Booth, and Francis 2007), 2015 (Pennebaker et al. 2015), and 2022 (Boyd et al. 2022).

The method has also been used widely across various academic studies and settings. These include studies of social media (Eichstaedt et al. 2018; Coppersmith, Harman, and Dredze 2014; Schwartz et al. 2013), news media (Horne and Adali 2017; Shu, Wang, and Liu 2019), online reviews (del Pilar Salas-Zárate et al. 2014), spam detection (Crawford et al. 2017).
The high-level idea is that given a set of normalized, stemmed words grouped into meaningful categories, such as negative emotion, conflict, or affiliation, one can count the occurrence of those words in a document to quickly assess what is being discussed in a document and how. In this work, we propose using this method as a mechanism for filtering and exploring the MeLa-BitChute dataset. By computing each LIWC category across all video titles, comments, and aggregating those scores by channels, we can effectively search for various types of content in the dataset, rather than searching using single keywords or manually exploring content across the many channels and videos.

To construct LIWC metadata, we use the latest version of LIWC: LIWC-22. Further documentation on LIWC22 can be found at [https://www.liwc.app/](https://www.liwc.app/), including definitions of all 117 categories. Below, we describe some examples using these categories, but do not define all categories included in the metadata.

3 Metadata Structure

Just as with the MeLa-BitChute dataset, we provide two widely-used data formats.

3.1 SQLite3 Database

The first format is an SQLite3 database with four tables:

1. **videos_liwc** - This table contains the video URL, title, profile, and channel, along with 117 LIWC categories calculated on each video title.
2. **comments_liwc** - This table contains anonymized user ID, video URL, comment ID, and parent ID, along with 117 LIWC categories calculated on each comment. User IDs are salted hashes of each user’s account information, allowing for comments to be grouped by users without revealing the username of the author. For more details on comment completeness and ID creation, see [Trujillo et al. 2022](https://www.liwc.app/)
3. **channel_comments_avgs_liwc** - This table contains the URL to the channel, the number of comments made on videos by the channel (called count), and the average of each LIWC category across all comments made on videos by the channel.
4. **channel_videos_avgs_liwc** - This table contains the URL to the channel, the number of videos by the channel (called count), and the average of each LIWC category across all video titles by the channel.

In Figure 1, we show both the MeLa-BitChute dataset schema and the LIWC metadata schema.

While both the original dataset and the metadata set can be used together, we choose to store each in independent databases for ease of use. Specifically, the video URLs, comment IDs and channel URLs can all be mapped back to the MeLa-BitChute dataset, but the needed text and URLs are also stored in the metadata set, allowing for exploration without joining the two databases. In Figure 1, we show how the two sets are related.

3.2 CSV

The second format in which we provide the dataset is a set of Comma-Separated Value (CSV) files. We provide four CSV files, one for each table in the database. The columns in each CSV file are the same as the columns in each corresponding SQLite3 database table.

4 Use Cases

There are several ways the MeLa-BitChute dataset can be explored using this metadata.

4.1 BitChute Compared to Itself and Other Social Platforms

First, using LIWC22 categories we can quickly examine if a channel or set of channels are producing content that is like other social platforms or not. In Table 1, we show the average and standard deviation of 17 LIWC categories across all of BitChute. These averages can be used as baselines to compare BitChute to other social platforms. For example, using Table 1, we can see that on average BitChute comments use more ‘negative tone’ (words such as bad, wrong, hate, etc.) than other social platforms such as Facebook, Reddit, Twitter, and online Blogs. We also see that the dispersion of negative tone scores across comments on BitChute is much higher than other social platforms. Similarly, we can see a higher use of ethnicity (words like Jew, American, French, Chinese, Indian, etc.) and religion (words like god, hell, christmas, church, etc.) in the comments on average than other platforms. When looking at the video titles, we see a higher use of conflict (words like fight, kill, killed, attack, etc.) and political words (words like United States, govern, congress, senate, etc.) on average than other platforms.

Second, we can use these LIWC baselines to compare individual channels to the rest of BitChute. For example, using the channel_videos_avgs_liwc database table, we see that the channel ‘banned-dot-video’, one of several Infowars channels on BitChute, uses more conflict words (1.79), power words (6.13), death words (1.16), and negative tone (5.43) in video titles than the rest of BitChute on average. Similarly, we can see video titles for channels like ‘zionistreport’, one of several anti-Semitic channels on BitChute, use more conflict words (0.97), ethnicity words (6.96), power words (7.04), death words (1.10), affiliation words (2.74), emotional anger (0.64) and negative tone (4.31) on average than the rest of BitChute video titles.

4.2 Ranking Channels, Comments, and Videos

These LIWC categories can also be used to rank channels by various word usages. For example, in Figures 4a, 4b, and 4c in Appendix D, we show rankings of channels by their average use of a LIWC category in the comments or video titles.

Using this ranking method we can find channels that have audiences who use high amounts of ethnicity words in the comments, pointing to channels such as ‘phoenix_party_fascists’ - an anti-Semitic channel that has
Figure 1: Metadata schema and original data schema. The original dataset tables are in purple, while the new metadata set tables are in red. The MeLa-Bitchute dataset and the metadata set are stored in standalone databases. To this end, the metadata tables include the text (titles or comment text) to allow for its use without the original dataset. Note, each metadata table contains 115 more LIWC category columns that are not shown to save space.

Table 1: Mean and Standard Deviation ($\mu \pm \sigma$) of selected LIWC22 categories across social platforms. Highlighted in bold red are the highest averages in each row. The column ‘BitChute Videos’ is the average LIWC category score across 3,036,190 video titles and the column ‘BitChute Comments’ is the average LIWC category score across 11,434,571 comments. The columns for Facebook, Reddit, Tweets, and Blogs are from the LIWC22 Test Kitchen Corpus (See here: [https://www.liwc.app/static/documents/LIWC-22.Descriptive.Statistics-Test.Kitchen.xlsx](https://www.liwc.app/static/documents/LIWC-22.Descriptive.Statistics-Test.Kitchen.xlsx)). A CSV file with all LIWC22 categories can be found on Dataverse.
since been blocked by BitChute due to ‘Platform Misuse’. Platform Misuse is a somewhat recent addition to the BitChute community guidelines - first appearing on the website in mid 2020. It states that channels can be blocked for behaviors such as brigading, metric manipulation, name squatting, scamming, or spamming. Importantly, it appears this channel was not blocked due to its anti-Semitic hate speech, but rather one of the listed platform misuses.

This ranking method also finds channels with particular psychological drives, such as use of power word words like own, order, allow, power, etc.) in the video titles. For example, in Figure 4e the top channel is Steve Bannon’s ‘pandemic war room’ - a channel that publishes Steven Bannon’s radio shows discussing everything from anti-intellectualism to COVID-19 conspiracy theories.

Importantly, when ranking by LIWC categories, one should provide a threshold for the number of comments or videos. For instance, if a channel has one video whose title uses all negative tone words, than it will have a ‘tone_neg’ score of 100 on average. However, since the channel only produced one video, being ranked highly in negative tone is probably not very meaningful. Instead, if we use the ‘count’ column in the database, we can filter to only rank channels that have more than a certain number of videos. See Table 6 in Appendix B for an example of this filter in SQL.

4.3 Exploring Topical Focuses on the platform
Several of the LIWC categories are topical in nature. For example, the categories ‘politic’ and ‘relig’ can show us what channels discuss politics and what channels discuss religion. When examining the rankings in Figure 4e and 4f in Appendix D, we can quickly see the top channels in each topic. For discussion of politics, we see channels such as ‘OANN’, the well-known far-right news network, and ‘DonaldJTrump’, a channel that publishes Donald Trump’s speeches. For discussion of religion, we see channels such as ‘StephenKJV1611’, the channel of Stephen Anderson1 and the channel ‘Church-Militant’, a claimed Catholic faith channel containing a variety of conspiracy theories.

5 Recommended Tools and Methods for Exploring the Metadata
Given the large size of the dataset and the complexity of various categories in LIWC, we recommend exploring and filtering the data using SQL. For those unfamiliar with SQL, we provide some plug-n-play examples of SQL statements for the metadata in Table 6 in Appendix B.

Furthermore, we recommend using SQLite DB Browser for easy exploration. In Figure 3 in Appendix C, we show screenshots of executing SQL and filtering columns by keywords in DB Browser. While we do provide the CSV versions of this metadata for use, it is likely too large to effectively explore in software like Excel on a typical laptop, while a database browser can handle the large size by not loading all the data at once.

6 Limitations
There are several important limitations of dictionary-based methods like LIWC that should be kept in mind when using this metadata.

First, the dictionaries are language specific. While the vast majority of BitChute is in English (Trujillo et al. [2020]), some channels are not. If the channel is not in English, the LIWC category values cannot be relied on. For example, if a channel is in German, the death category in LIWC will be high, as the German word for ‘the’ is ‘die’. This limitation may slightly inflate the average use of ‘death’ words across the platform.

Second, it is well known that in fringe communities, language may be used in community-specific ways not captured by LIWC. While LIWC has an extensive ‘netspeak’ category, it is unlikely this covers all of the dog-whistles and coded language used by fringe groups. For example, the use of triple parenthesis around a word, such as (((jew))) or (((they))), in fringe communities often refers to anti-Semitic conspiracy theories and contexts (Zannettou et al. [2020]). These types of coded languages are not captured by LIWC. Although the word ‘jew’ appears to be captured in both the ethnicity and religion categories, words such as ‘they’ are simply captured as 3rd person plural words.

Third, while LIWC has been validated in many settings, dictionary-based methods naturally lose the context around individual words. For example, two comments may use the same word in the category ‘death’ - one comment may be a call to violence, while the other may be discussing the Biblical theology of death. These contextual differences should be taken into account when interpreting aggregate results. This limitation has also been noted in other studies (Hirsh and Peterson [2009]; Bantum and Owen [2009]).

7 Conclusion
In this paper, we describe a LIWC metadata set for use in exploration and sub-setting the MeLa-BitChute dataset. We provide multiple levels of metadata, including LIWC scores for video titles, comments, and aggregations of both per channel. In addition, we provide averages of each category across the full platform to provide baselines for comparing channels to the rest of BitChute and to other social media platforms. Lastly, we provide example plug-in-play SQL statements for exploring the metadata and a guide to using the SQLite DB Browser.

Our hope is that this metadata can better support qualitative researchers and investigative journalist in the use of the MeLa-BitChute dataset, and that it can provide LIWC baselines for researchers to compare other alt-tech platforms to BitChute.

Both the original MeLa-BitChute dataset and the metadata described in this paper can be found in the following repository: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/KRD1VS

1Stephan Anderson is known for anti-homosexual hate speech and has been banned from several countries, read more here: https://en.wikipedia.org/wiki/Steven_anderson_(pastor)
   https://sqlitebrowser.org/
A Data Column Descriptions

In this section, we provide descriptions of each data column in the MeLa-BitChute supplemental metadata. Below are tables for each table in the database (videos_liwc, comments_liwc, channels_comments_avg_liwc, and channels_videos_avg_liwc).

Note, to save space, we do not list each LIWC category. However, all 117 LIWC categories are included with the same names as provided by LIWC. For a detailed description of each, please see https://www.liwc.app/.

| Column Name | Description |
|-------------|-------------|
| url         | URL to video |
| title       | Title of the video |
| profile     | URL to the uploader’s profile. Note, a profile can have multiple channels, but a channel belongs to one profile. |
| channel     | URL to the channel |

All LIWC categories 117 columns corresponding to each LIWC category. The column names are the same as the names found in the LIWC documentation. Each LIWC category is a number between 0 and 100, representing a percent of text that falls in that category. Please note baselines can vary widely for LIWC categories based on the size of the dictionary.

Table 2: videos_liwc data description.

| Column Name | Description |
|-------------|-------------|
| url         | URL to video that the comment falls under |
| userid      | A SHA256 hash that uniquely identifies each commenter |
| posttext    | The body text of the comment (a pre-processed version of posthtml in the original dataset) |
| comment_id  | A text ID identifying a comment on a video |
| parent_id   | If non-NULL, refers to the comment_id of the parent comment |

All LIWC categories 117 columns corresponding to each LIWC category. The column names are the same as the names found in the LIWC documentation. Each LIWC category is a number between 0 and 100, representing a percent of text that falls in that category. Please note baselines can vary widely for LIWC categories based on the size of the dictionary.

Table 3: comments_liwc data description.

| Column Name | Description |
|-------------|-------------|
| channel     | URL to the channel |
| count       | Number of comments on videos by the channel |

The average LIWC score of comments on videos by the channel, done for all 117 LIWC categories. The column names are the same as the names found in the LIWC documentation.

Table 4: channels_comments_avg_liwc data description.

| Column Name | Description |
|-------------|-------------|
| channel     | URL to the channel |
| count       | Number of videos by the channel |

The average LIWC score of video titles by the channel, done for all 117 LIWC categories. The column names are the same as the names found in the LIWC documentation.

Table 5: channels_videos_avg_liwc data description.
### B SQL Examples

In the section, we provide several example SQL statements that can be used to explore the dataset. In each example, LIWC categories can be replaced by any other LIWC category.

| SQL statement                                                                 | Description                                                                                                                                                                                                 |
|-------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| SELECT channel, title, ethnicity FROM videos
  WHERE WC >= 5 ORDER BY ethnicity DESC LIMIT 500                            | Returns the channel url, video title, and ethnicity LIWC score ranked by the highest use of ethnicity words in the title, where title has at least 5 words. The LIWC category ‘ethnicity’ can be replaced with any LIWC category. We recommend limiting your output when exploring due to the large size of what will be returned. |
| SELECT url, posttext, ethnicity FROM comments
  WHERE WC >= 10 ORDER BY ethnicity DESC LIMIT 500                           | Returns the video url, comment text, and ethnicity LIWC score ranked by the highest use of ethnicity words in the comment, where comment has at least 10 words. The LIWC category ‘ethnicity’ can be replaced with any LIWC category. |
| SELECT channel, power FROM channel_video_avgs
  WHERE count >= 1000 ORDER BY power DESC LIMIT 500                         | Returns channels ranked by average use of power words in video titles where the channel has at least 1000 videos. The LIWC category ‘power’ can be replaced with any LIWC category.                                           |
| SELECT channel, conflict, ethnicity, tone_neg, power, death, emo_anger from channel_video_avgs
  WHERE channel = '/channel/zionistreport/'                                | Returns average LIWC scores for conflict, ethnicity, negative tone, power, death, and emotional anger from video titles produced by the channel ‘zionistreport’. LIWC categories and channel name can be replaced with desired categories and channel name. |
| SELECT channel, conflict, ethnicity, tone_neg, power, death, emo_anger from channel_comments_avgs
  WHERE channel = '/channel/banned-dot-video/'                              | Returns average LIWC scores for conflict, ethnicity, negative tone, power, death, and emotional anger from comments under videos by the channel ‘banned-dot-video’. LIWC categories and channel name can be replaced with desired categories and channel name. |
| SELECT channel, conflict FROM channel_comments_avgs
  WHERE count >= 100 ORDER BY conflict DESC LIMIT 500                       | Returns channels ranked by average use of conflict words in comments where the channel has at least 100 comments. The LIWC category ‘conflict’ can be replaced with any LIWC category.                                           |
| SELECT videos_liwc.channel, comments_liwc.posttext, comments_liwc.death FROM comments
  JOIN videos_liwc ON comments_liwc.url = videos_liwc.url
  WHERE comments_liwc.WC >= 100 ORDER BY comments_liwc.death DESC LIMIT 500 | Returns the channel url and comment text ranked by the number of death words in a single comment, where the comment contains at least 100 words. The LIWC category ‘death’ can be replaced with any LIWC category. |
| SELECT url, posttext, ethnicity from comments
  WHERE ethnicity > 0.90                                                     | Returns all comments that contain more ethnicity words than the average BitChute comment.                                                                                                                  |
| SELECT channel, url, conflict from videos
  WHERE conflict > 0.82                                                      | Returns all videos with titles that contain more conflict words than the average BitChute video.                                                                                                           |

Table 6: Example SQL queries for easy, plug-n-play exploration of the metadata.
C  DB Browser Examples

In the section, we provide screenshots of different ways to use DB Browser (https://sqlitebrowser.org/). Namely, to execute SQL and to filter columns by a single keyword.

Figure 2: Screenshot of DB Browser SQL query screen. To explore dataset, open database in DB Browser, navigate to the Execute SQL tab, write or copy SQL query into middle box, and press the green play button. One can examine the columns and structure of each table in the database by using the Database Structure tab.

Figure 3: Screenshot of DB Browser ‘Browse Data’. To explore dataset, open database in DB Browser, navigate to the Browse Data SQL tab, type keyword to filter data by in the desired column. For example, to get all tables with the word ‘banned’ we can filter the channel column.
D Example Channel Rankings

(a) Channels ranked by use of ‘ethnicity’ words in comments

(b) Channels ranked by use of ‘tone_neg’ words in comments

(c) Channels ranked by use of ‘conflict’ words in video titles

(d) Channels ranked by use of ‘power’ words in video titles

(e) Channels ranked by use of ‘relig’ words in video titles

(f) Channels ranked by use of ‘politic’ words in comments

Figure 4: In (a) we show the top 20 channels ranked by the use of ethnicity words in comments on average, for channels with at least 500 comments. In (b) we show the top 20 channels ranked by the use of negative tone words in comments on average, for channels with at least 500 comments. In (c) we show the top 20 channels ranked by the use of conflict words in video titles on average, for channels with at least 500 videos. In (d) we show the top 20 channels ranked by the use of power words in video titles on average, for channels with at least 500 videos. In (e) we show the top 20 channels ranked by the use of religion words in video titles on average, for channels with at least 500 videos. In (f) we show the top 20 channels ranked by the use of political/politics words in comments on average, for channels with at least 500 comments. Note, in each we only show the first 25 characters of channel names for the visualization.
References

Allport, G. W. 1942. The use of personal documents in psychological science. Social Science Research Council Bulletin.

Althoff, T.; Jindal, P.; and Leskovec, J. 2017. Online actions with offline impact: How online social networks influence online and offline user behavior. In Proceedings of the tenth ACM international conference on web search and data mining, 537–546.

Bantum, E. O.; and Owen, J. E. 2009. Evaluating the validity of computerized content analysis programs for identification of emotional expression in cancer narratives. Psychological assessment, 21(1): 79.

Boyd, R. L.; Ashokkumar, A.; Seraj, S.; and Pennebaker, J. W. 2022. The Development and Psychometric Properties of LIWC22.

Cannava, K. E.; High, A. C.; Jones, S. M.; and Bodie, G. D. 2018. The stuff that verbal person-centered support is made of: Identifying linguistic markers of more and less supportive conversations. Journal of Language and Social Psychology, 37(6): 656–679.

Coppersmith, G.; Harman, C.; and Dredze, M. 2014. Measuring post traumatic stress disorder in Twitter. In Eighth international AAAI conference on weblogs and social media.

Crawford, M.; Khoshgoftaar, T. M.; Prusa, J. D.; Richter, A. N.; and Al Najada, H. 2015. Survey of review spam detection using machine learning techniques. Journal of Big Data, 2(1): 1–24.

del Pilar Salas-Zárate, M.; López-López, E.; Valencia-García, R.; Aussenas-Gilles, N.; Almela, A.; and Alor-Hernández, G. 2014. A study on LIWC categories for opinion mining in Spanish reviews. Journal of Information Science, 40(6): 749–760.

Donovan, J.; Lewis, B.; and Friedberg, B. 2019. Parallel ports: Sociotechnical change from the alt-right to alt-tech.

Eichstaedt, J. C.; Smith, R. J.; Merchant, R. M.; Ungar, L. H.; Crutchley, P.; Preoijuc-Pietro, D.; Asch, D. A.; and Schwartz, H. A. 2018. Facebook language predicts depression in medical records. Proceedings of the National Academy of Sciences, 115(44): 11203–11208.

Flaxman, S.; Goel, S.; and Rao, J. M. 2016. Filter bubbles, echo chambers, and online news consumption. Public opinion quarterly, 80(S1): 298–320.

Francis, M.; and Booth, R. J. 1993. Linguistic inquiry and word count. Southern Methodist University: Dallas, TX, USA.

Guess, A.; Nyhan, B.; Lyons, B.; and Reifler, J. 2018. Avoiding the echo chamber about echo chambers. Knight Foundation, 2: 1–25.

Hirsh, J. B.; and Peterson, J. B. 2009. Personality and language use in self-narratives. Journal of research in personality, 43(3): 524–527.

Horne, B.; and Adali, S. 2017. This just in: Fake news packs a lot in title, uses simpler, repetitive content in text body, more similar to satire than real news. In Proceedings of the international AAAI conference on web and social media, volume 11, 759–766.

Jasser, G.; McSwiney, J.; Pertwee, E.; and Zannettou, S. 2021. ‘Welcome to# GabFam’: Far-right virtual community on Gab. New Media & Society, 1461448211024546.

Larcker, D. F.; and Zakolyukina, A. A. 2012. Detecting deceptive discussions in conference calls. Journal of Accounting Research, 50(2): 495–540.

Munn, L. 2021. More than a mob: Parler as preparatory media for the US Capitol storming. First Monday.

Pennebaker, J.; Booth, R.; and Francis, M. 2007. Linguistic Inquiry and Word Count: LIWC2007—Operator’s Manual. LIWC. net.