Global Network
on Extremism & Technology

A Picture is Worth a Thousand (S)words: Classification and Diffusion of Memes on a Partisan Media Platform

Ayse D. Lokmanoglu, Mowafak Allaham, Rod M. Abhari, Chloe Mortenson and Esteban Villa-Turek

March 2023

GNET is a special project delivered by the International Centre for the Study of Radicalisation, King's College London.

The authors of this report are Ayse D. Lokmanoglu, Mowafak Allaham, Rod M. Abhari, Chloe Mortenson and Esteban Villa-Turek

Center for Communication and Public Policy, Northwestern University, Evanston IL, USA

The Global Network on Extremism and Technology (GNET) is an academic research initiative backed by the Global Internet Forum to Counter Terrorism (GIFCT), an independent but industry-funded initiative for better understanding, and counteracting, terrorist use of technology. GNET is convened and led by the International Centre for the Study of Radicalisation (ICSR), an academic research centre based within the Department of War Studies at King's College London. The views and conclusions contained in this document are those of the authors and should not be interpreted as representing those, either expressed or implied, of GIFCT, GNET or ICSR.

CONTACT DETAILS

For questions, queries and additional copies of this report, please contact:

ICSR
King's College London
Strand
London WC2R 2LS
United Kingdom

T. **+44 20 7848 2098**
E. **mail@gnet-research.org**

Twitter: **@GNET_research**

Like all other GNET publications, this report can be downloaded free of charge from the GNET website at www.gnet-research.org.

Recommended citation:
Lokmanoglu, Ayse D., Mowafak Allaham, Rod Abhari, Chloe Mortenson, and Esteban Villa-Turek. "A Picture Is Worth a Thousand (S)Words: Classification and Diffusion of Memes on a Partisan Media Platform." London: Global Network on Extremism and Technology (GNET), March 2023. https://doi.org/10.18742/pub01-117.

Executive Summary

Memes have become an integral tool of communication in partisan online spaces.[1] Internet memes are defined as "a group of digital items sharing a common characteristic … created with awareness of each other … circulated imitated and/or transformed via the internet by many users."[2] There has been extensive research on the impact and properties of misinformation, as well as methods for platforms to moderate misinformation. However, moderation policies and algorithms capable of filtering out meme content with extremist foundations are lacking. Moderating supremacists' memes through algorithms is difficult as images are not as easily detectable as text. Moreover, memes often embody inside jokes among users or have an unassuming image form that hides political intent.[3] Building on prior research on identification of terrorist imagery, this report explores algorithmic approaches to classifying harmful meme content and exploring their patterns of diffusion.[4]

Using state-of-the-art deep learning image and visual rhetorical analysis, we examine memes on an alternative (or fringe) platform by categorising them into themes of gender, race, partisanship and violence. This method further reveals the transmission rates of the memes associated with these themes. We propose a unique methodology that combines automatic image clustering with network analysis, developing a framework to compare the transmission rates of memes at different timepoints. In so doing, we provide experts with a working model of meme content filtering to help platforms to identify and filter memes with supremacist topics; the model also allows for the testing of image attributes to aid the development of a toolkit to understand which memes are spread in alt-tech platforms.

The key findings are:

- There is no direct correlation between engagement and the number of memes in a topic cluster.
- Memes with intersectional themes of gender and race with partisanship had the highest virality and diffusion.
- In 2020, the five meme clusters with the highest impact factors were Climate Change, George Soros, Pro-Trump 1, Pro-Trump 2,

1 Heather Suzanne Woods and Leslie Ann Hahner, *Make America Meme Again: The Rhetoric of the Alt-Right*, Frontiers in Political Communication, vol. 45 (New York: Peter Lang, 2019); Angela Nagle, *Kill All Normies: The Online Culture Wars from Tumblr and 4chan to the Alt-Right and Trump* (Winchester, UK; Washington, USA: Zero Books, 2017); Hampton Stall, Hari Prasad and David Foran, 'Can the Right Meme? (And How?): A Comparative Analysis of Three Online Reactionary Meme Subcultures', Year 2 (The Global Network on Extremism and Technology (GNET), 13 December 2021), https://gnet-research.org/2021/12/13/can-the-right-meme-and-how-a-comparative-analysis-of-three-online-reactionary-meme-subcultures/.

2 Limor Shifman, *Memes in Digital Culture*, MIT Press Essential Knowledge (Cambridge, Massachusetts: The MIT Press, 2014): 41.

3 An Xiao Mina, 'Batman, Pandaman and the Blind Man: A Case Study in Social Change Memes and Internet Censorship in China', *Journal of Visual Culture* vol. 13, no. 3 (December 2014): 359–75, https://doi.org/10.1177/1470412914546576.

4 The report examines memes distributed within an alternative platform; thus the report includes images of memes that are highly offensive, racist, misogynist and Islamophobic. The authors include this trigger warning for the readers.

and Michelle Obama. By way of comparison, in 2021, five clusters on Maga and Soldiers, Against Political Lobbying, Children and Gender, Leftists, and Missing Votes had the highest impact factor.

- The degree of violence and the transmission rate of violent memes increased, starting mid-2020 up to January 2021.
- Memes with high engagement levels often were branded by a group emblem or logo.

Contents

1 Introduction

Misinformation, conspiracy theories and supremacist content have often been addressed at the textual level of social media posts, blogs, conspiracy theory articles and speeches.[5] However, a picture is worth a thousand words: visual supremacist content can be more effective and flexible than text alone. Supremacist groups abundantly employ visuals in whole or part as their messaging content, utilising photographs, manipulated images, infographics, cartoons, memes, logos and videos.[6] Visuals function as critical pieces of a messaging strategy, as they are not bound by language restrictions, have higher levels of attraction and recall, and provide neural shortcuts that can maximise viewer identification with displayed in-group beliefs.[7]

The online space creates opportunities for supremacist actors to deploy image symbols as defining elements of their emergent communities. Unlike text, visual objects do not require an audience to have obtained a certain level of literacy, making them more accessible to global audiences.[8] Images serve as effective vehicles for conveying messages and narratives, as audiences respond to visual messaging with higher levels of attention and recall.[9] Images are also easier to process cognitively, more likely to elicit emotional responses and more often interpreted as believable; they also allow audiences to relate to the displayed in-group beliefs. Furthermore, images aid the formation of both individual identity and the identity of a group, specifically by being the symbol of a group's core ideology.[10]

---

5 We would like to thank Erik Nisbet, the Director of the Center for Communication and Public Policy (CCPP) at Northwestern University for all his support, mentorship and guidance throughout this project. We would also like to thank Alexander Phelan, Craig Whiteside, Carol Winkler and members of the CCPP Lab.

6 Amarnath Amarasingam, Shiraz Maher and Charlie Winter, 'How Telegram Disruption Impacts Jihadist Platform Migration' (Centre for Research and Evidence on Security Threats, January 2021), https://icsr.info/wp-content/uploads/2021/01/How-Telegram-Disruption-Impacts-Jihadist-Platform-Migration.pdf; Lokmanoglu et al., 'ISIS Media and Troop Withdrawal Announcements'; Hampton Stall, David Foran and Hari Prasad, 'Kyle Rittenhouse and the Shared Meme Networks of the Armed American Far-Right: An Analysis of the Content Creation Formula, Right-Wing Injection of Politics, and Normalization of Violence', *Terrorism and Political Violence* (22 June 2022): 1–25, https://doi.org/10.1080/09546553.2022.2074293; Michael Waltman, 'Teaching Hate: The Role of Internet Visual Imagery in the Radicalization of White Ethno-Terrorists in the United States', in *Visual Propaganda and Extremism in the Online Environment*, ed. Carol Winkler et al. (Carlisle, PA: Strategic Studies Institute and U.S. Army War College Press, 2014): 83–104.

7 Doris A. Graber, 'Seeing Is Remembering: How Visuals Contribute to Learning from Television News', *Journal of Communication* 40, no. 3 (September 1990): 134–56, https://doi.org/10.1111/j.1460-2466.1990.tb02275.x; Robin L. Nabi, 'Exploring the Framing Effects of Emotion: Do Discrete Emotions Differentially Influence Information Accessibility, Information Seeking, and Policy Preference?', *Communication Research* 30, no. 2 (April 2003): 224–47, https://doi.org/10.1177/0093650202250881; Waltman, 'Teaching Hate: The Role of Internet Visual Imagery in the Radicalization of White Ethno-Terrorists in the United States'.

8 Graber, 'Seeing Is Remembering'; Lokmanoglu et al., 'ISIS Media and Troop Withdrawal Announcements'; Ayse Lokmanoglu, 'Coin as Imagined Sovereignty: A Rhetorical Analysis of Coins as a Transhistorical Artifact and an Ideograph in Islamic State's Communication', *Studies in Conflict & Terrorism* vol. 44, no. 1 (16 July 2020): 1–22, https://doi.org/10.1080/1057610X.2020.1793458.

9 Ann Marie Barry, *Visual Intelligence: Perception, Image, and Manipulation in Visual Communication* (Albany: State University of New York Press, 1997); Marwan Kraidy, 'The Projectilic Image: Islamic State's Digital Visual Warfare and Global Networked Affect', *Media, Culture & Society* vol. 39, no. 8 (2017): 1,194–1,209, https://doi.org/10.1177/0163443717725575; Annie Lang, John Newhagen and Byron Reeves, 'Negative Video as Structure: Emotion, Attention, Capacity, and Memory', *Journal of Broadcasting & Electronic Media* vol. 40, no. 4 (September 1996): 460–77, https://doi.org/10.1080/08838159609364369; Lokmanoglu et al., 'ISIS Media and Troop Withdrawal Announcements'; John E. Newhagen and Byron Reeves, 'The Evening's Bad News: Effects of Compelling Negative Television News Images on Memory', *Journal of Communication* vol. 42, no. 2 (1 June 1992): 25–41, https://doi.org/10.1111/j.1460-2466.1992.tb00776.x.

10 Kareem El Damanhoury, 'Constructing Place Identity: ISIS and Al-Qaeda's Branding Competition over the Caliphate', *Place Branding and Public Diplomacy* (2019), https://doi.org/10.1057/s41254-019-00155-1; Lokmanoglu, 'Coin as Imagined Sovereignty'; Charlie Winter, 'Framing War: Visual Propaganda, the Islamic State, and the Battle for East Mosul', *Cambridge Review of International Affairs* (29 January 2020): 1–23, https://doi.org/10.1080/09557571.2019.1706074; Aaron Y. Zelin, 'Picture Or It Didn't Happen: A Snapshot of the Islamic State's Official Media Output', *Perspectives on Terrorism* vol. 9, no. 4 (21 July 2015), http://www.terrorismanalysts.com/pt/index.php/pot/article/view/445; Nagle, *Kill All Normies*; Woods and Hahner, *Make America Meme Again*; Robert Hariman and John Louis Lucaites, *No Caption Needed: Iconic Photographs, Public Culture, and Liberal Democracy* (Chicago: University of Chicago Press, 2007).

In this report we address the loophole that visual supremacist content exploits; namely, that visual supremacist content cannot easily be detected by standard classification approaches. Since memes are effective supremacist messaging vehicles, it is imperative that an algorithmic approach to identification of harmful memes is developed and that the spread of this content is explored.

In that vein, we have three objectives:

- Develop an algorithmic capability to identify categories of harmful meme content;
- Describe the level of user engagement with harmful meme content; and,
- Explore the extent to which such memes are diffused on fringe social media networks, normalising hateful rhetoric.

2 Literature Review: Memes as 'Supremacist' Messaging

The digital world has created hyper-connected transnational public spheres providing an ideal venue for individuals across the ideological spectrum to develop interests in and interactions with supremacist movements and like-minded individuals.[11] Through its ability to deliver visualised objects and other messaging content to global audiences, this domain enables the reproduction of cultural markers that expand upon those associated with supremacist messaging.

The internet is an open space for individuals to find and connect with like-minded people. The environment does not require direct physical interaction with users, as it functions as part of daily conversations. While this feature has contributed to the success of the internet, it has also allowed ill-intentioned actors to establish a primary communication channel with target audiences.[12] The online environment allows such individuals or groups to overcome the hurdles of traditional media governance and content moderation policies to disseminate their messages cheaply, easily, anonymously and widely.[13]

The role of messaging in ideology, public discourse and community-building processes focus primarily on discursive communication (that is, social media posts, manifestos and digital magazines) and more recently on nondiscursive communications (images, videos and songs).[14] Accordingly, supremacist persuasive messaging, specifically that of racist, misogynist and ethno-religious separatist nature, serves as an illuminating case where supremacist groups can contribute and shape public discourse around sensitive topics and build communities of supporters online within mainstream platforms.[15] While in this study we focus on examining right-wing supremacist communications contained within our dataset, the theoretical framework developed herein holds true for other extremist or supremacist groups.

11 Dror Walter et al., 'Ideologize Globally, Mobilize Locally: The Internationalization of Far-Right Online Discourse' (International Communications Associations (ICA), virtual, 2021).
12 Gabriel Weimann, 'The Theater of Terror: The Psychology of Terrorism and the Mass Media', *Journal of Aggression, Maltreatment & Trauma* vol. 9, no. 3–4 (18 April 2005): 379–90, https://doi.org/10.1300/J146v09n03_08; Maura Conway, Ryan Scrivens and Logan Macnair, 'Right-Wing Extremists' Persistent Online Presence: History and Contemporary Trends', *ICCT Policy Brief* (October 2019); Carol Winkler and Ayse Lokmanoglu, 'Communicating Terrorism and Counterterrorism', in *The Handbook of Communication and Security*, ed. Bryan C. Taylor and Hamilton Bean, First edition, International Communication Association (Ica) Handbook Series (New York, NY: Routledge, 2019): 381–98.
13 Amarasingam, Maher and Winter, 'How Telegram Disruption Impacts Jihadist Platform Migration'; Kayla McMinimy et al., 'Censoring Extremism: Influence of Online Restriction on Official Media Products of ISIS', *Terrorism and Political Violence* (10 November 2021): 1–17, https://doi.org/10.1080/09546553.2021.1988938; Kayla McMinimy and Ayse Lokmanoglu, 'Censoring Extremism: Impact of Takedowns on Islamic State Visuals', *Global Network on Extremism & Terrorism (GNET)* (blog) (26 November 2021), https://gnet-research.org/2021/11/26/censoring-extremism-impact-of-takedowns-on-islamic-state-visuals/; Winkler and Lokmanoglu, 'Communicating Terrorism and Counterterrorism'.
14 Winkler and Lokmanoglu, 'Communicating Terrorism and Counterterrorism'; Bart Schuurman, 'Research on Terrorism, 2007–2016: A Review of Data, Methods, and Authorship', *Terrorism and Political Violence*, March 2018: 1–16, https://doi.org/10.1080/09546553.2018.1439023; Maura Conway and Stuart Macdonald, 'Introduction to the Special Issue: Extremism and Terrorism Online – Widening the Research Base', *Studies in Conflict & Terrorism* (21 January 2021): 1–7, https://doi.org/10.1080/1057610X.2020.1866730.
15 Winkler and Lokmanoglu, 'Communicating Terrorism and Counterterrorism'; Schuurman, 'Research on Terrorism, 2007–2016'; Conway and Macdonald, 'Introduction to the Special Issue'.

Studies looking at right-wing extremism (RWE) on the internet demonstrate ideological convergence and connections to offline behaviour, predominantly focusing on the textual content within and across platforms. For example, Scrivens et al. revealed in their examination of the mobilisation efforts within each Iron March and Fascist Forge online content (n=4,000) that the advocacy and encouragement of violence "was the top mobilization indicator".[16] Similarly, Tien et al. computed the level of polarisation in Twitter conversations about the 'Unite the Right' rally in 2017 in Charlottesville, Virginia, and identified white supremacist messages to be unifying.[17] De Koster and Houtman, pursuing a systematic qualitative analysis within Stormfront.org coupled with online interviews with users of the forum, found that the community formation revolved around the core ideology of white supremacism.[18] Other studies, looking at topics about science within Stormfront.org, concur with De Koster and Houtman's findings, specifically on how the community forms around the white supremacist ideology despite topical variations within the conversations.[19]

While these studies have generated useful insights on the messaging and participation in online right-wing spaces, they are by no means limited purely to ideological or violent discussions. A recent analysis of one Stormfront.org subforum showed that nearly 65% of discussion dealt with "banal" issues related to everyday life.[20] Involvement in these online conversations provides an "inherent reward" in that an individual gains a sense of belonging and the in-group feels defined.[21] However, by participating in these communities, individuals become part of a space where supremacist messaging is normalised alongside banal messages, even if supremacist messages represent a small proportion of the content.[22] Thus, it is crucial to examine other forms of messaging that shape public discourse, especially those that incorporate other forms besides text.

Memes, Public Discourse & Community Building

A meme functions as a humorous, visual illustration that replicates and moves along cultural information ecosystems via human interaction.[23] Internet memes can be understood as "a group of digital items sharing a common characteristic … created with awareness of each other … circulated, imitated and/or transformed via the internet by many users."[24] Milner described memes as "universal and particular, familiar and

16 Ryan Scrivens et al., 'Examining Online Indicators of Extremism in Violent Right-Wing Extremist Forums', *Studies in Conflict & Terrorism* (6 May 2021): 1–25, https://doi.org/10.1080/1057610X.2021.1913818.

17 Joseph H. Tien et al., 'Online Reactions to the 2017 "Unite the Right" Rally in Charlottesville: Measuring Polarization in Twitter Networks Using Media Followership', *Applied Network Science* vol. 5, no. 1 (December 2020): 1–27, https://doi.org/10.1007/s41109-019-0223-3.

18 Willem De Koster and Dick Houtman, '"STORMFRONT IS LIKE A SECOND HOME TO ME": On Virtual Community Formation by Right-Wing Extremists', *Information, Communication & Society* vol. 11, no. 8 (December 2008): 1,155–76, https://doi.org/10.1080/13691180802266665.

19 Yotam Ophir et al., 'Weaponizing Reproductive Rights: A Mixed-Method Analysis of White Nationalists' Discussion of Abortions Online', *Information, Communication & Society* (27 June 2022): 1–26, https://doi.org/10.1080/1369118X.2022.2077654; Dror Walter et al., 'Vaccine Discourse in White Nationalist Online Communication: A Mixed-Methods Computational Approach', *Social Science & Medicine* 298 (1 April 2022): 114859, https://doi.org/10.1016/j.socscimed.2022.114859.

20 Yannick Veilleux-Lepage, Alexandra Phelan, and Ayse D. Lokmanoglu, 'Gendered Radicalisation and "Everyday Practices": An Analysis of Extreme Right and Islamic State Women-Only Forums', *European Journal of International Security* (5 December 2022): 1–16, https://doi.org/10.1017/eis.2022.32.

21 Richard English, *Does Terrorism Work? A History*, First edition (Oxford, United Kingdom; New York, NY: Oxford University Press, 2016).

22 Daniel Karell et al., 'Hard-Right Social Media and Civil Unrest', preprint (SocArXiv, 5 May 2021), https://doi.org/10.31235/osf.io/pna5u.

23 Benjamin Lee, '"Neo-Nazis Have Stolen Our Memes": Making Sense of Extreme Memes', in *Digital Extremisms: Readings in Violence, Radicalisation and Extremism in the Online Space*, ed. Mark Littler and Benjamin Lee, Palgrave Studies in Cybercrime and Cybersecurity (Cham, Switzerland: Palgrave Macmillan, 2020): 91–108, https://doi.org/10.1007/978-3-030-30138-5.

24 Shifman, *Memes in Digital Culture*: 41.

foreign", as "small expressions with big implications."[25] The transformative and participatory functions of memes make them not only vehicles of persuasive messaging but also building blocks for the creation of online group cultures.[26] The scholarship on supremacist images lacks emphasis on user-generated content that has been created, amended and shared by digital audiences that contribute to public discourse.

Memes supporting digital cultures have been analysed through a variety of classifications. Wiggins and Bowers argue that memes act as a genre, as they have a participatory and generative function within digital culture connected to social action, starting from their initial spread to their realisation as a meme proper. Wiggins and Bowers insist that "memes are remixed and iterated messages which are rapidly spread by members of participatory digital culture".[27] Milner further elaborates on memes as participatory culture within the digital world and demonstrates how memes shape public conversations.[28] Both studies show how memes act as digital objects with a participatory function that are easily spreadable within similar digital cultures.

In addition to their participatory function, memes can be persuasive tools of communication. Woods and Hahner, in their study of right-wing memes in 4chan around the 2016 presidential election in the United States, demonstrated how memes function as persuasive tools within public discourse.[29] They described several instances from the Unite the Right Rally in Charlottesville, Virginia, where one of the main organisers and several participants discussed memes as tactical tools.[30] Other studies focusing on 4chan and memes further elaborated on their persuasiveness within public culture, including in such areas as activism.[31] Furthermore, previous studies have discovered the dynamic and participatory nature of memes, moving and transforming public discourse from the extreme to the mainstream.[32] Thus a meme is not only a symbolic representation of digital culture but also an evolving digital object that shapes discourse. Integrating the meme characteristics highlighted in previous studies, our report defines supremacist memes as *participatory digital objects* and *persuasive messages* that *shape public discourse* and *evoke motivations of activism*.

The de-platforming of accounts sharing extremist ideologies (that is, far right and salafi-jihadist) has resulted in users migrating to alternative platforms.[33] For example, in their comparative study of right- and left-wing online activism, Freelon et al. highlighted the platform migration of some far-right users to "alt-tech equivalents", including Parler, Gab and BitChute.[34] These platforms have become attractive as they have more relaxed content moderation protocols in comparison to mainstream platforms such as Twitter and Facebook, meaning that

25 Milner, *The World Made Meme*: 14.
26 Woods and Hahner, *Make America Meme Again*.
27 Bradley E. Wiggins and G. Bret Bowers, 'Memes as Genre: A Structurational Analysis of the Memescape', *New Media & Society* vol. 17, no. 11 (December 2015): 1,886–1,906, https://doi.org/10.1177/1461444814535194.
28 Milner, *The World Made Meme*.
29 Woods and Hahner, *Make America Meme Again*.
30 ibid., 30.
31 Asaf Nissenbaum and Limor Shifman, 'Internet Memes as Contested Cultural Capital: The Case of 4chan's /b/ Board', *New Media & Society* vol. 19, no. 4 (April 2017): 483–501, https://doi.org/10.1177/1461444815609313; Woods and Hahner, *Make America Meme Again*; Nagle, *Kill All Normies*.
32 Woods and Hahner, *Make America Meme Again*.
33 Amarasingam, Maher and Winter, 'How Telegram Disruption Impacts Jihadist Platform Migration'; Deen Freelon, Alice Marwick and Daniel Kreiss, 'False Equivalencies: Online Activism from Left to Right', *Science* vol. 369, no. 6,508 (4 September 2020): 1,197–1,201, https://doi.org/10.1126/science.abb2428; McMinimy et al., 'Censoring Extremism'; Richard Rogers, 'Deplatforming: Following Extreme Internet Celebrities to Telegram and Alternative Social Media', *European Journal of Communication* vol. 35, no. 3 (June 2020): 213–29, https://doi.org/10.1177/0267323120922066.
34 Freelon, Marwick and Kreiss, 'False Equivalencies': 3.

"they allow partisan and fringe communities to exist without opposition from alternative viewpoints".[35] Digital fascism manipulates and takes advantages of social media and open digital societies to expand and to create new ideologically focused ecosystems.[36] In the Zannettou et al. study examining Gab over eighteen months, the authors found that the proportion of hate speech on the platform was 2.4 times higher than that of Twitter.[37] Studies on ideologically like-minded social media platforms mostly examine Stormfront.org, 4chan, IronMarch and other platforms and forums that define themselves as white supremacist.[38] These sites allowed researchers to harvest and employ data for further research around supremacist rhetoric and visuals, and their associations with offline factors.

Despite these studies, there is a scarcity of moderation policies and algorithmic capabilities available to filter out memes with politically, racially and religiously charged material from mainstream social media. For example, even in China where censorship algorithms are strict, politically charged memes are often not caught by filters because they often embody inside jokes among users or have an unassuming image form that hides the political intent.[39]

A meme with supremacist content has the potential to become polarising and motivating when it spreads and turns into social contagion. Social contagion is the spread of memes or ideas through personal contact; social media enables high levels of personal contact across wide geographies without the loss of intimacy that once attended such great distances.[40] Applied in the extremist context, memes allow audiences with supremacist sympathies to connect with others, to grow polarised and to become motivate towards possible actionable outcomes in a more efficient way. An example of this can be found in how the alt-right in the United States has used memes to spread extremist views.[41] Several major figures in alt-right communities have endorsed memes both as methods of normalising extremist views and as effective rhetoric.[42]

---

35 ibid.

36 Maik Fielitz and Holgar Marcks, 'Digital Fascism: Challenges for the Open Society in Times of Social Media', CRWS Working Papers (Berkeley, CA: UC Berkeley: Center for Right-Wing Studies, 16 July 2019), https://escholarship.org/uc/item/87w5c5gp.

37 Savvas Zannettou et al., 'What Is Gab: A Bastion of Free Speech or an Alt-Right Echo Chamber', in *Companion of the The Web Conference 2018 on The Web Conference 2018 – WWW '18* (Companion of the The Web Conference 2018, Lyon, France: ACM Press, 2018): 1,008, https://doi.org/10.1145/3184558.3191531.

38 N. Caren, K. Jowers and S. Gaby, 'A Social Movement Online Community: Stormfront and the White Nationalist Movemen', in *Media, Movements, and Political Change*, ed. Jennifer S. Earl and Deana A. Rohlinger (Emerald Group Publishing, 2012); Tammy Castle and Meagan Chevalier, 'The Women of Stormfront: An Examination of White Nationalist', *Internet Journal of Criminology* (2011), https://www.internetjournalofcriminology.com/_files/ugd/b93dd4_19a87177897a4ab2b18fa8ffc2bb7f48.pdf; De Koster and Houtman, '"STORMFRONT IS LIKE A SECOND HOME TO ME"'; Stephanie L. Hartzell, 'Whiteness Feels Good Here: Interrogating White Nationalist Rhetoric on Stormfront', *Communication and Critical/Cultural Studies* vol. 17, no. 2 (2 April 2020): 129–48, https://doi.org/10.1080/14791420.2020.1745858; Nagle, *Kill All Normies*; Ophir et al., 'Weaponizing Reproductive Rights'; Ryan Scrivens et al., 'Sugar and Spice, and Everything Nice? Exploring the Online Roles of Women in the Far-Right Extremist Movement' (Conference Presentation, Vox-Pol, Amsterdam, Netherlands, 21 August 2018), https://www.voxpol.eu/wp-content/uploads/2018/09/2018-VOX-Pol-Conference-Role-of-RWE-Women-PPT.pdf; Ryan Scrivens, Garth Davies and Richard Frank, 'Searching for Signs of Extremism on the Web: An Introduction to Sentiment-Based Identification of Radical Authors', *Behavioral Sciences of Terrorism and Political Aggression* vol. 10, no. 1 (2 January 2018): 39–59, https://doi.org/10.1080/19434472.2016.1276612; Walter et al., 'Vaccine Discourse in White Nationalist Online Communication'; Veilleux-Lepage, Phelan and Lokmanoglu, 'Gendered Radicalisation and "Everyday Practices"'.

39 Mina, 'Batman, Pandaman and the Blind Man'.

40 J. M. Berger, 'The Metronome of Apocalyptic Time: Social Media as Carrier Wave for Millenarian Contagion', *Perpectives of Terrorism* vol. 9, no. 4 (2015): 11.

41 We define the term 'alt-right' as an umbrella term encompassing individuals and groups espousing a combination of xenophobic, homophobic, racist, Islamophobic, anti-Semitic, anti-system (that is, anti-government, anti-democracy), ethnonationalist or anti-immigrant, misogynist, or fascist/authoritarian beliefs, attitudes and actions from Cynthia Miller-Idriss, *The Extreme Gone Mainstream: Commercialization and Far Right Youth Culture in Germany*, Princeton Studies in Cultural Sociology (Princeton: Princeton University Press, 2018) and Cas Mudde, *The Far Right Today* (Cambridge, UK: Polity Press, 2019).

42 Some examples: Lee, '"Neo-Nazis Have Stolen Our Memes": Making Sense of Extreme Memes'; L. Murray, 'On Normies', 2016, http://therightstuff.biz/2016/06/02/on-normies/; V. Day, 'Tears of a Cuck', 2016, http://voxday.blogspot.co.uk/2016/10/tears-of-cuck.html. Please note that both these blogs have been removed. References to these blogs can be found in Littler and Lee, *Digital Extremisms: Readings in Violence, Radicalisation and Extremism in the Online Space*: 91–108.

Stall et al., in one of the first large-N studies to examine right-wing memes about Kyle Rittenhouse, developed a methodology to classify memetic messaging according to their aesthetics.[43] This study's analysis and classification demonstrated that memes used a common language among social media users sympathising with Rittenhouse and espousing far-right views. DeCook similarly demonstrated how memes distributed within the digital sphere of the men's rights organisation the Proud Boys functioned as language vehicles for identification and socialisation, showing insights into the youth culture and ideology construction within the group.[44] As discussed in these studies and many others, memes created and shared in 'extreme' digital spaces travel to less extreme spaces and continue their expansion of public discourse.

Memes within the space of digital online media become an integral part of the participatory digital culture in extremist-supremacist places. Due to their nature – "collective, creative, constitutive and capable of influencing others" – they represent important markers of public discourse; they are embedded within the particular culture.[45] Nagle meticulously examined Pepe Le Frog, Trumpian, Harambe and other memes within 4chan as important vehicles of culture creation within alt-right audiences, emphasising the roles of meme-making and meme distribution as tactics in the culture wars.[46] Similarly, Woods and Harris stated that "circulation of Alt-right memes is the cardinal feature of their impact on public culture".[47] We specifically focus on how political memes are engaged with and diffused within these communities. Subsequently, the user engagement of the meme is as integral to the function of the meme in public discourse as the meme content itself is.

Thus, this report tackles the following questions:

1. How can we identify memes within more moderate and partisan alternative platforms targeting general audiences and what is the predominant content of these memes?
2. What content and themes of memes generate the highest engagement?
3. What content and themes of memes spread faster and in more diffuse ways?

43 Stall, Foran and Prasad, 'Kyle Rittenhouse and the Shared Meme Networks of the Armed American Far-Right'.
44 Julia R. DeCook, 'Memes and Symbolic Violence: #proudboys and the Use of Memes for Propaganda and the Construction of Collective Identity', *Learning, Media and Technology* vol. 43, no. 4 (2 October 2018): 485–504, https://doi.org/10.1080/17439884.2018.1544149.
45 Woods and Hahner, *Make America Meme Again*: 49.
46 Nagle, *Kill All Normies*.
47 Woods and Hahner, *Make America Meme Again*: 11.

3 Methods

In this section, we describe the dataset used in this report, the methodology employed to identify memes with similar content and the qualitative analysis and assessment carried out of most engaging memes clusters (figure 1).

Figure 1: Methodology Flow

Data

Our research aim is to provide a mixed-method toolkit that facilitates the analysis of memes found on alternative platforms. To use ethically scraped data and test our methods, we utilised a publicly available dataset of Parler posts collected by Aliapoulios et al. between August 2018 and January 2021 to explore and identify meme content on Parler.[48] The dataset consisted of 183.1 million Parler posts made by 4.08 million users. The dataset also included metadata for each post, such as a unique identifier per post, the time stamp of when a post was created, the user account associated with the post, engagement data per post characterised by the number of upvotes, comments and reposts, and the post content itself (text and URLs).

According to the Pew Research Institute, "Parler is the best known of the seven alternative social media sites … with 38% of U.S. adults saying they have heard of it."[49] Parler is a microblogging social network that launched in August 2018. It publicised its platforms with the byline "Speak Freely", attracting users unsatisfied with the content moderation on mainstream platforms.[50] Parler markets itself as aiming to "provide an unbiased platform where users can engage in civil discourse without fear of ideological censorship".[51] Parler served as the optimal pilot dataset for developing and testing our methodology, as it provided the following:

- An alternative social media platform where the discourse was closer to mainstream media, as the platform did not define itself with supremacist ideology, instead opting for, simply, "free speech".

48 Max Aliapoulios et al., 'A Large Open Dataset from the Parler Social Network' (Zenodo, 15 January 2021), https://doi.org/10.5281/ZENODO.4442460; Max Aliapoulios et al., 'An Early Look at the Parler Online Social Network' (arXiv, 18 February 2021), http://arxiv.org/abs/2101.03820. The data collection ends January 2021, due to Parler switching servers after 6 January 2021.
49 Carrie Blazina and Galen Stocking, 'Key Facts about Parler', *Pew Research Center* (blog), 20 October 2022, https://www.pewresearch.org/fact-tank/2022/10/20/fast-facts-about-parler-as-kanye-west-reportedly-plans-acquisition-of-site/.
50 'Join the Premier Global Free Speech App | Parler', Parler, 23 January 2023, https://parler.com.
51 Parler, 'What Is the Parler Community Jury?', *Parler* (blog), 1 December 2022, https://blog.parler.com/what-is-the-parler-community-jury/.

- The platform data included time stamps, engagement (upvotes, downvotes and reposts).

- The platform did not have accessibility interruptions from its establishment until the end of our data collection.

To extract memes from Parler posts, all URLs to images were retrieved from the metadata fields of the 183.1 million posts. Only 3% of the posts had images (6,626,622 images). Approximately 92% of these images (6,148,168) are no longer available or accessible. This could be due to Parler switching servers in 2021.[52] Out of the remaining 478,454 images, 2.7% (13,225) of these images were excluded from our analysis because the files were distorted. The total number of remaining images to be included in the analysis was 465,229 images.

Image Clustering

We used a combination of computational and qualitative methods to a) group images thematically into image clusters based on content similarity and b) examine the generated clusters to determine the types of topics present in the most engaging memes clusters.[53] To group similar images thematically into clusters called concepts, we used ConceptModel, a model that combines CLIP (Contrastive Language Image-Pretraining) and BERTopic (a variation of Bidirectional Encoder Representations from Transformers for topic modelling) to perform concept modelling on images.[54] ConceptModel accepts pairs of images and documents (that is, keywords or phrases) associated with each image to find the best words for each concept. Since we did not have an a priori set of categories into which to fit the memes, we passed only the images to the CLIP model in ConceptModel in a Zero-Shot prediction approach.[55]

ConceptModel uses CLIP to create image embeddings (a lower dimensional representation of an image) for all images. Afterwards, UMAP (Uniform Manifold Approximation and Projection for Dimension Reduction) was applied to further reduce the dimensionality of image embeddings to pass them to the HDBSCAN (High Density-Based Spatial Clustering of Applications with Noise) clustering algorithm. HDBSCAN clusters the low-dimensional embeddings from UMAP to create clusters of images that were like each other. Once images were grouped in clusters, concepts were constructed by extracting examples of images that are most relevant to each cluster, as shown in figure 2.

52 John Paczkowski and Ryan Mac, 'Amazon Is Booting Parler Off Of Its Web Hosting Service', BuzzFeed News, 9 January 2021, https://www.buzzfeednews.com/article/johnpaczkowski/amazon-parler-aws.
53 The code for the analysis is available on https://github.com/nwccpp/meme-project.
54 Maarten Grootendorst, 'BERTopic', Python, 24 October 2022, https://github.com/MaartenGr/BERTopic; Maarten Grootendorst, 'Concept', Python, 6 January 2023, https://github.com/MaartenGr/Concept.
55 Alexandre Alcoforado et al., 'ZeroBERTo: Leveraging Zero-Shot Text Classification by Topic Modeling', vol. 13208, 2022, 125–36, https://doi.org/10.1007/978-3-030-98305-5_12.

Figure 2: Example of nine concepts, each containing a set of images that were clustered together on account of being similar.

Labelling the Most Engaging Memes Clusters

To identify the themes of memes generating the highest user engagement in our dataset, we first had to pair our findings from image clustering with engagement data from the metadata file by retrieving the number of upvotes and reposts that each image has received. Accordingly, we amended the metadata file for the subset of images we were analysing to include the cluster to which each image belongs based on the ConceptModel output. This allowed us to analyse the volume of meme clusters over time (figure 3) and facilitated the analysis of user engagement with specific meme clusters. More importantly, this enabled us to select the most engaging memes clusters and qualitatively analyse their content to identify the topics covered by these clusters. (Labels included 'extremist', 'violent', 'political', 'climate change', and others. For a more detailed explanation of the clusters see appendix A.1)[56]

56 For an example of each meme for each cluster please contact the authors for access to appendix B. Due to the supremacist content within memes, appendix B will only be available upon request.

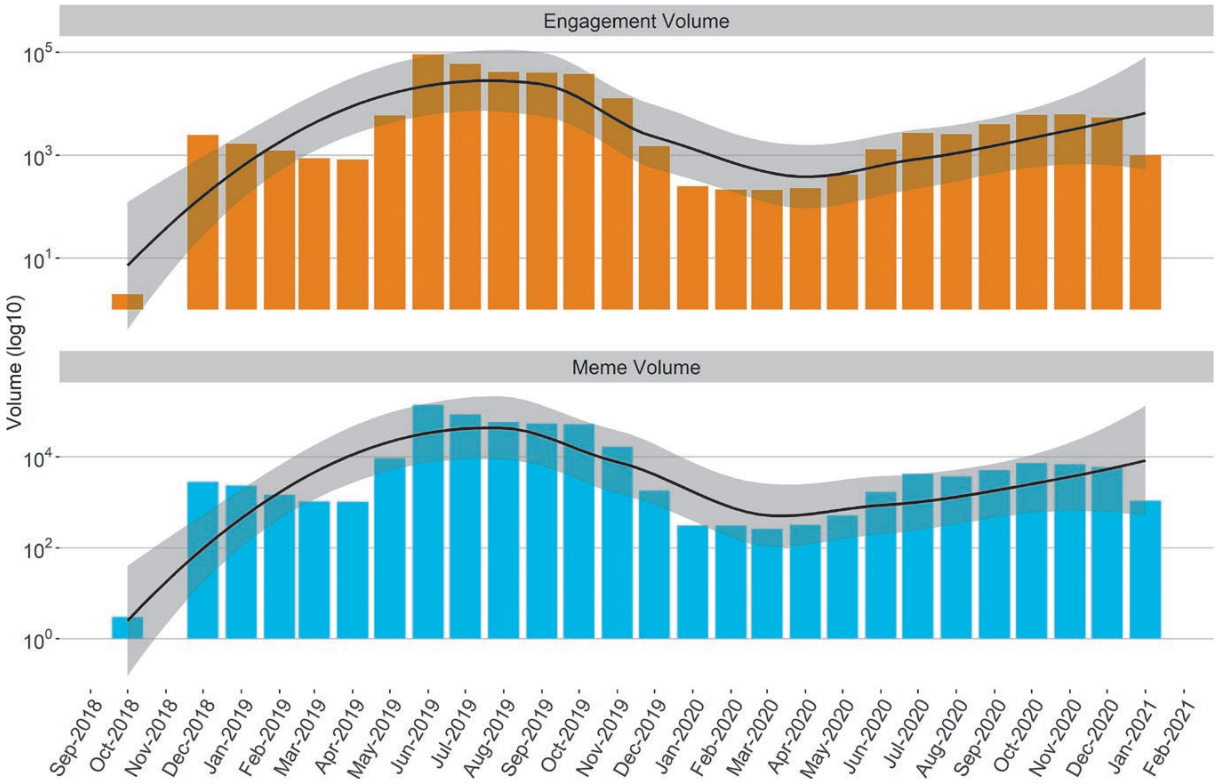

Figure 3: Monthly Volume of Memes and Engagement with the Memes (upvotes and reposts). For visualisation purposes the y-axis has been scaled to log10.[57]

To analyse and label the content of each cluster, we selected only clusters that fell within our definition of memes:

1. A digital image, created or repurposed to amend or alter its meaning into a message.
2. It includes an image and text.
3. It is created to be circulated.

We manually coded the meme content of the top 25 clusters that generated the most engagement from each of the years 2019, 2020 and 2021, a total of 75 clusters. Next, to be able to label the themes for each cluster, we sampled 25 images from each cluster and hand-coded for the presence of gender, race, violence and partisanship content in each cluster, which also gave us an insight into the type of discourse circulating on Parler via these images. We defined the presence of themes as follows:

- Gender: Any presence of non-cis-male gender and appeals to masculinity (for example, women, LGBTQ+, the effeminising of men).
- Race: Any presence of non-white (minority) racial content (for example, Hispanic, Middle Eastern, Black).
- Violence: Any presence of violence or threats of violence (such as a knife, castration, death and veiled threats).
- Partisanship: Any presence of political partisanship (such as use of words like Democrat, Republicans, Liberals, Antifa).

57 The decadic algorithm or Log10 calculations on the y axis values are used to provide a better visualisation for data with great variations. The calculation for decadic algorithm is Y = log10(X).

Analysing the Dynamics of Engagement

The observed variance in the volume of memes and their respective level of engagement over time and across different themes led us to hypothesise that such cultural products experience both gradual and abrupt changes in their popularity. For example, memes that centre longstanding in-jokes or ubiquitous icons (such as Donald Trump) may feature relatively constant engagement, while memes about current events (such as American Independence Day) might spike and recede rapidly. Therefore, analysing the dynamics of engagement for the most engaging memes can reveal key features about the user behaviour and cultural makeup of the alternative platform.

By comparing the number of users who engage with each meme ensemble (that is, each cluster of memes on the same theme), we can further analyse memes that make up Parler's dominant culture at various points in time. This helps to generate insights about the varying levels of engagement with memes during important national events, such as the United States presidential elections or the days leading up to the 6 January insurrection. In addition, by analysing the dynamics of engagement, we can reveal how specific political events may have influenced or shaped the discourse on the alternative platform.

To analyse these dynamics, we created a dynamic network graph of the 50 most shared clusters of memes and visualised the changes in total engagement at different points in time. The network graph is a *co-share graph* where memes, represented as labels, are connected based on the number of users in common that share them at a given time. This is a local measure of engagement that shows the amount of user overlap between memes. In addition, labels are scaled to reflect the total amount of engagement within a meme cluster. This is a global measure of engagement that depicts the amount of engagement received by memes across time.

We also created a measure for consistency of engagement (that is, the median of monthly engagement) to identify the memes that were most consistently popular with Parler users. The median, which is robust to outliers, is preferred to the mean for the purposes of measuring consistency of engagement. Memes with consistent engagement across time will generally have a higher monthly median engagement score than those that receive inconsistent engagement. Accordingly, the duration of a meme's popularity is used to identify the core memes that constitute the culture of Parler.

Diffusion of Memes

For the purposes of meme sharing on Parler, we conceptualise 'diffusion' as the process by which memes are spread between users through posts on Parler. Core concepts in diffusion that we analyse are 'exposure' and 'transmissibility'. As the chief mechanism behind the spread of information, analysing diffusion is one key to understanding why violent Parler memes go viral.

In an epidemiological model, exposure is measured by the number of users who come into contact with a given contagious infection. For social network data, however, measuring exposure is complicated by the fact that the true number of users who viewed content is generally unknown. Although our data contains information about users' interactions with memes, these users are a subset of the number of users who actually viewed a meme in the first place. With this limitation in mind, we can infer exposure based on the posting activity of users.

On forums, a post that receives comments is referred to as a thread. To measure exposure, we make the conservative assumption that users who comment on a thread where a meme has already been shared will have been exposed to it. This assumption is especially reasonable for smaller threads, where a commenter can easily read the previous comments before commenting. Leveraging this assumption, we produce a sample of exposures to each meme by collecting the users that comment on a thread after a meme has been posted.

To analyse the spread of memes, we measure the transmissibility of each meme cluster. Transmissibility is an indicator of the ability of a contagion to infect the individuals exposed to it. We measure transmissibility by calculating the proportion of users who shared a meme after commenting on it on a thread:

$$\textit{Transmission Rate of a meme} = \frac{\textit{\# of meme shares}}{\begin{array}{c}\textit{\# of comments on the thread}\\ \textit{following the meme post}\end{array}}$$

In other words, the transmission rate is equal to the number of users who commented on a thread with the meme and then shared it divided by the number of users who solely commented on a thread with the meme regardless of whether they shared it. While this approach is unable to account for exposure to memes shared as the last post in a thread, or those memes shared that had previously received no comments, it succeeds in creating reliable diffusion pathways for every meme cluster in our sample.

Limitations

Due to the nature of memes and the size of the data we faced some limitations during the project. First, because memes can contain both images and text, they are more difficult than images alone to identify automatically. Thus, we had to integrate human coders to identify if a cluster was a meme cluster. Likewise, visual software struggled to identify supremacist themes because mainstream supremacist memes often do not use weapons or blood, instead using mockery, such as threatening language, racism and sexism, to disseminate supremacist ideology. Furthermore, automatically judging the level of violence within each meme was not feasible as violence was presented in different forms. As a result, we relied on our human coders to identify the supremacist content as well as the level of violence within the meme clusters. None of these would have been feasible without the computing resources offered by the Center for Communication and Public Policy and Northwestern University's Quest Computing Services, as we needed computing and cloud resources beyond 100 GB to process and analyse the data.

4 Findings

Image Clustering

All 465,229 images were divided into 2,669 clusters. ConceptModel clustered 54% (251,506 images) of all images into 2,668 clusters and the remaining 45% (213,723 images) were grouped under a single cluster. This behaviour is expected in clustering algorithms due to the large sample of images and the wide variety of content. Figure 4 presents the distribution of images across 2,668 clusters, discounting the outlier cluster with 45% of images.

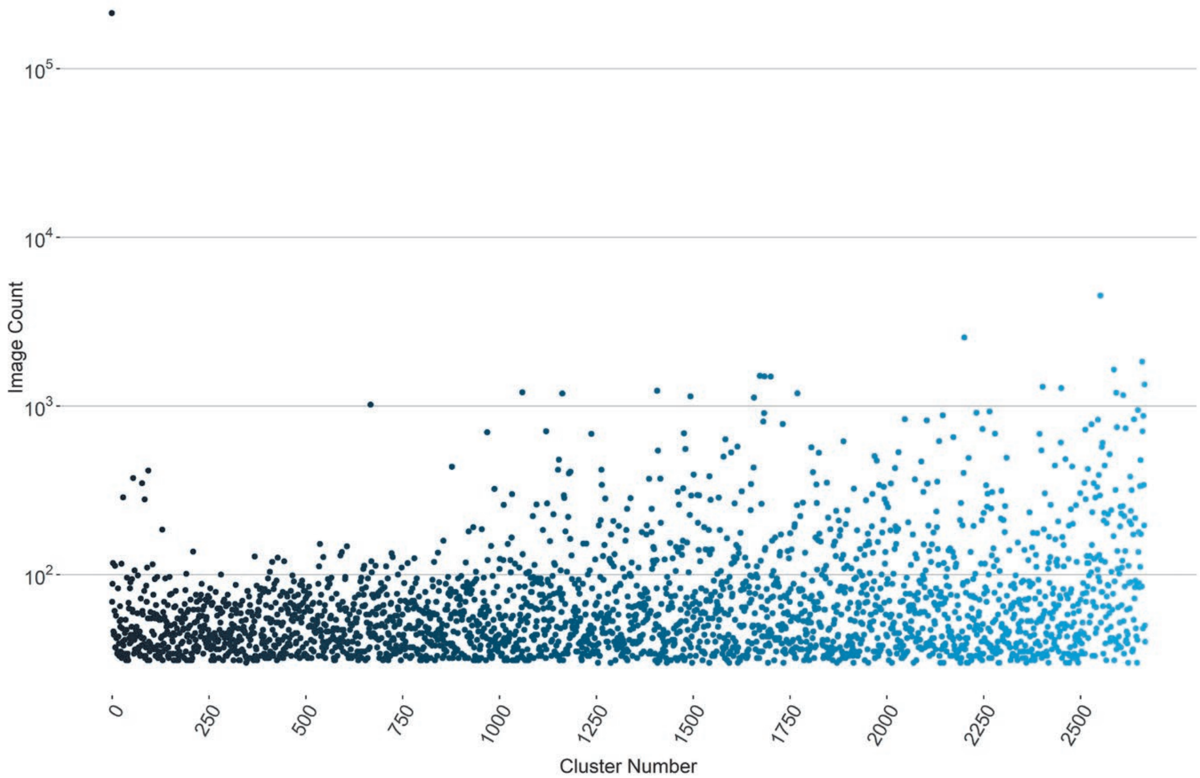

Figure 4: Distribution of image counts per cluster (from Cluster 0 to Cluster 2,668).

Labelling the Most Engaging Memes Clusters

Descriptive statistics showed that memes are not artistically elaborate. Rather, they are mostly as simple as a combination of some writing with a stock image or photo. The ones that were more elaborate were branded by the content creators. The intersectional topics of gender and race were the most violent in terms of imagery, while partisanship-only topics had the least violent imagery qualitatively according to our coders (see table A.2). Clusters of gender and partisanship, such as Effeminizing Biden Voters, had more visually unpleasant content including impressions of female and male genitalia (see appendix B.1 for meme examples). We also examined the aggregate engagement for each of the themes.

The topic labelling showed that the overall top 25 most engaged clusters in 2019 were mainly focused on political figures and political events (figure 5). The clusters represented 2.12% of all engagement and consisted of topics strongly associated with right-wing politics, including President Trump's Election, Gun Rights, Antifa and Veterans, Congress, and General Flynn.

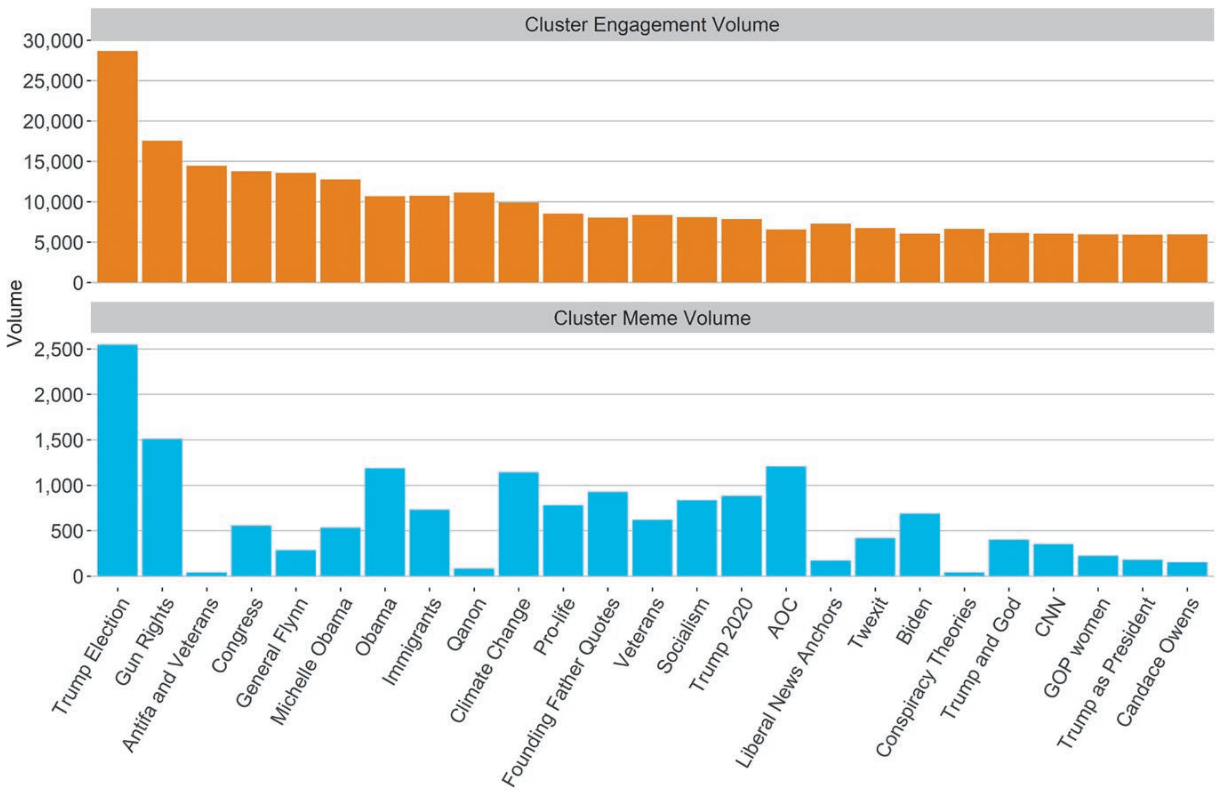

Figure 5: Top 25 Most Engaged Clusters in 2019.

In 2020, the top 25 clusters focused on partisanship and election fraud, with a strong undercurrent of conspiracy theory. The five clusters with the most engagement were Pro-Trump, George Soros's Son, Political Cartoons, John Kerry Climate and Election Fraud/Biden (figure 6). Even though the actual volume of memes in these categories was small, especially the Pro-Trump and George Soros's Son categories, the engagement with these memes was strong, indicating that they were more viral. The rest of the top clusters focused on Pro-Trump 2, Political Tweets, Political Conspiracy and Pelosi. As seen in figure 7, the clusters were predominantly partisan.

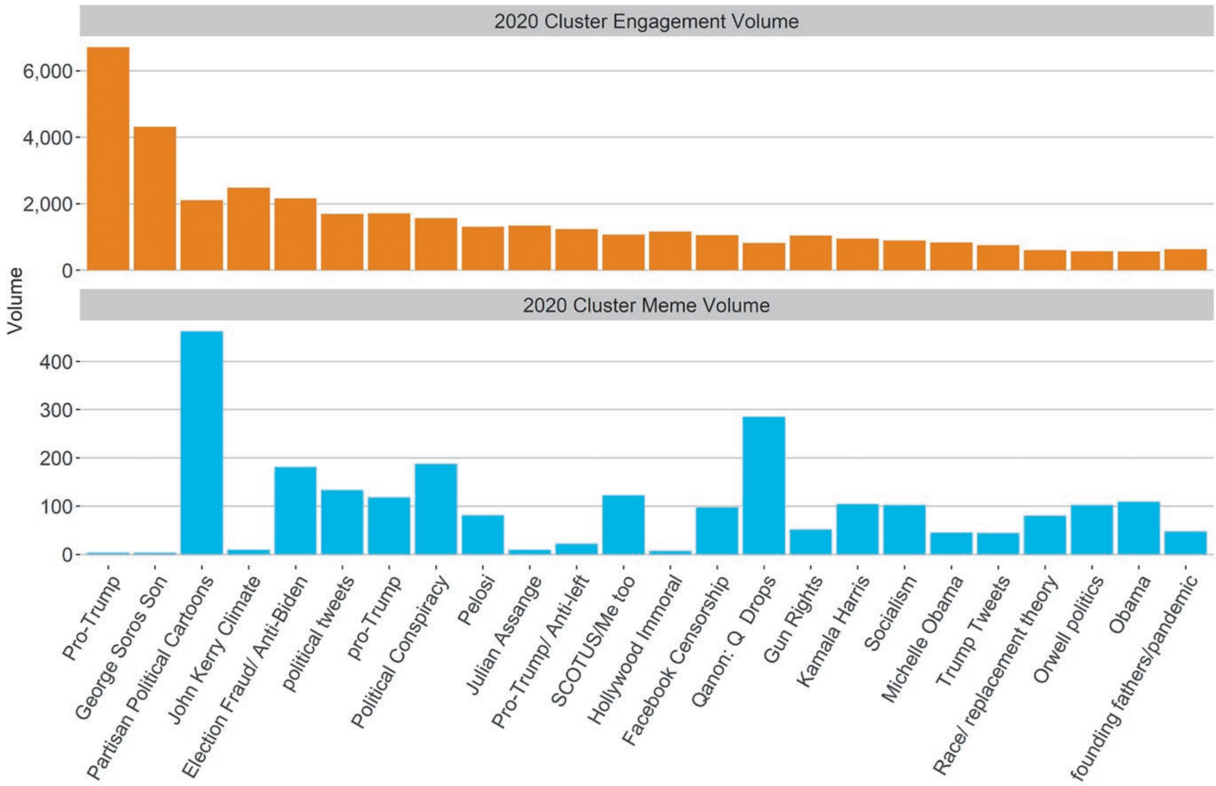

Figure 6: Top 25 Most Engaged Clusters in 2020.

As for January 2021, the top 25 clusters focused on partisanship topics. The five clusters with most engagement was Government Shutdown, Leftist, Lobbying, Against Propaganda (Democrat Propaganda) and True Americans. The rest of the top clusters focused on the democratic party, election denialism and Trumpian topics (figure 7). It is important to note that the dataset collection ends after 6 January 2021, which limits the top 25 clusters in 2021 to less than a month.

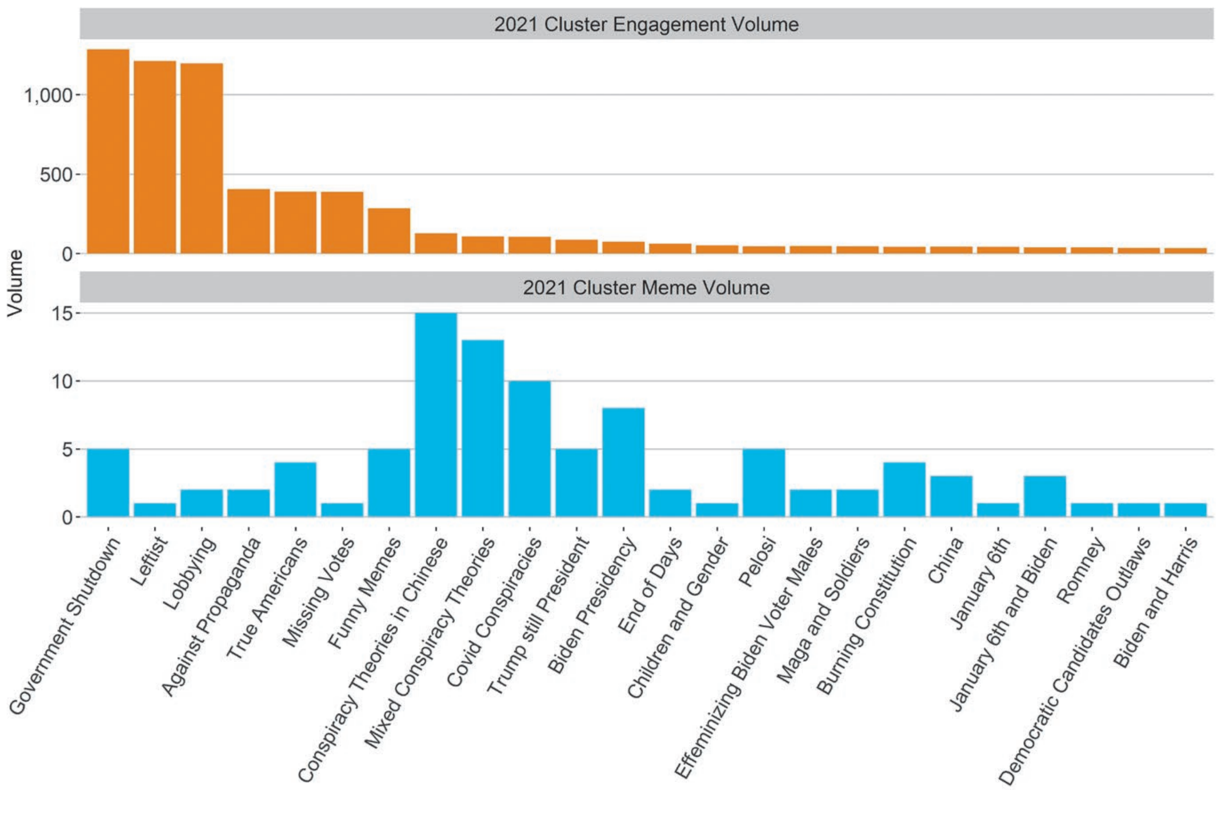

Figure 7: Top 25 Most Engaged Clusters in January 2021.

In the thematic trendline of these 75 clusters we can see that partisanship has the highest monthly engagement (figure 8). For the violence, race and gender themes, there is a steep increase after February, March and April 2020 respectively. This increasing trend in the race and gender themes continues until November 2020, whereas the violence theme continues to increase until January 2021. A similar increasing trend occurred previously from April to June 2019.

Figure 8: Aggregate Monthly Engagement for Themes.

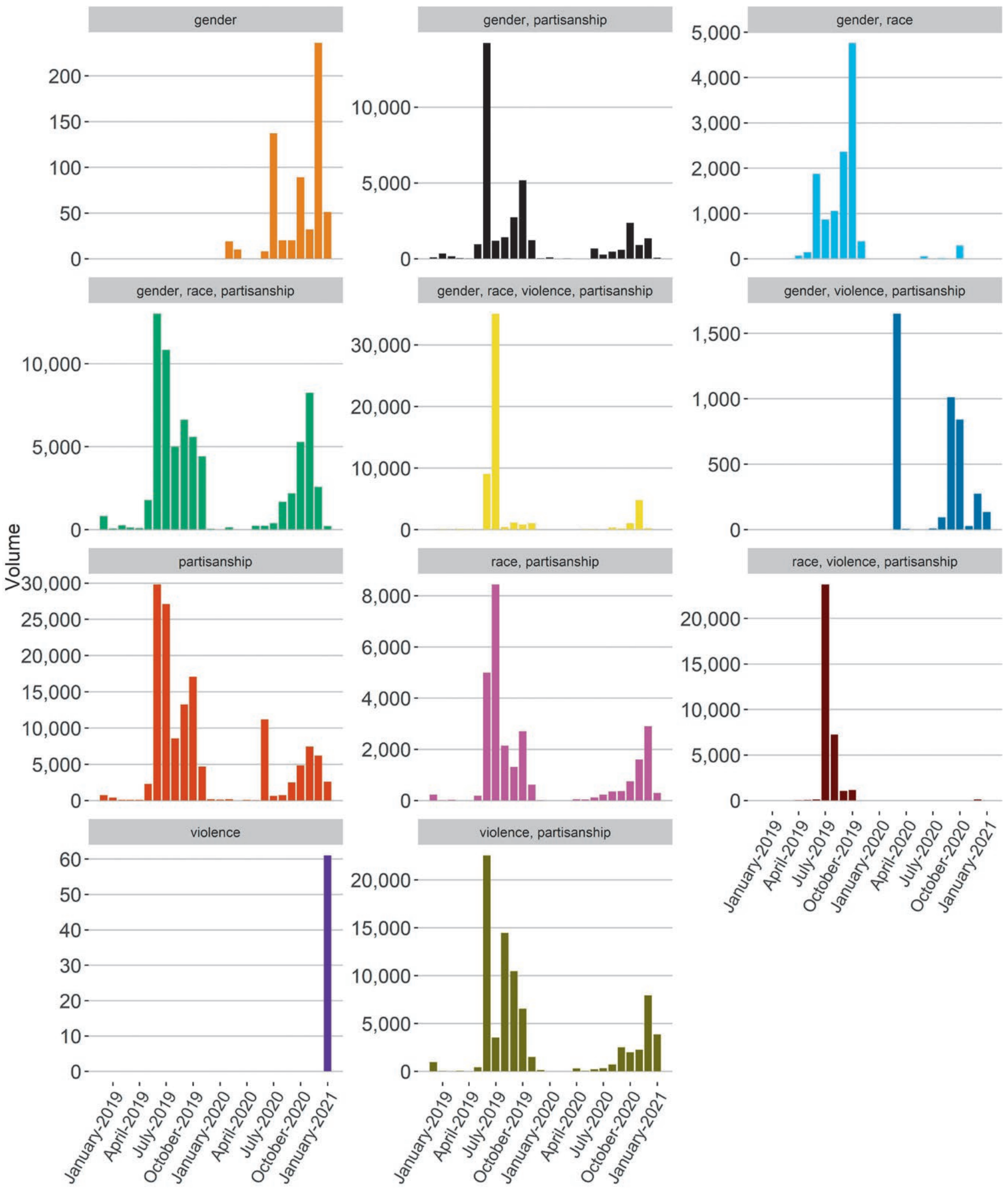

Figure 9: Monthly Aggregate Engagement by Intersectional Themes.

Memes that were labelled by an intersectional theme involving gender, race, violence and partisanship had the highest monthly engagement of 35,060 of all themes in July 2019 (figure 9). By further analysing the themes in our 75 coded clusters, we found that memes were targeting two individuals: Michelle Obama (see figure 11 and appendix B.1 for examples) and Nancy Pelosi.

Between December 2018 and January 2021, as shown in figure 8, partisanship memes had more engagement over time compared to other memes of different themes. This can partially be attributed to the number of clusters that fit the partisanship theme during the manual coding of these themes. Second and third highest engagement in a single month over the timeframe was the partisanship cluster with 29,779 in June 2019 and 27,107 in July 2019, which included a multitude of clusters (see table A.1 in Appendix A).

After partisanship, the highest engagement in a single month was the intersectional theme of race, violence and partisanship with an engagement of 23,715, again in July 2019, associated with the Qanon cluster. The fifth theme with the highest single monthly engagement was violence and partisanship, which consisted of a multitude of clusters including Jan 6th, Qanon Q Messages, Conspiracy Theories, Gun Rights and Socialism, generating an engagement of 22,534 in June 2019 (see table A.1 for all clusters within each theme).

Analysing the Dynamics of Engagement

We picked three key dates in the Parler timeline to examine dynamic engagement: 1 January 2019 (the start date for our Parler data), 3 November 2020 (US presidential election) and 6 January 2021 (USA Capitol Hill insurrection). Three patterns of engagement appear among memes (figure 10). First, there are memes with gradual changes in attention. Biden memes began generating engagement in the late spring of 2020 and steadily increased throughout the election season. This can easily be explained by the fact that Joseph Biden was the presumptive Democratic nominee by April 2020 and campaigned against Donald Trump in the 2020 general election. Former president Barack Obama and former first lady Michelle Obama received considerable attention from memes in the same period. This is likely due to the association of Biden as the former vice president under Obama, and with the Democratic party more generally.

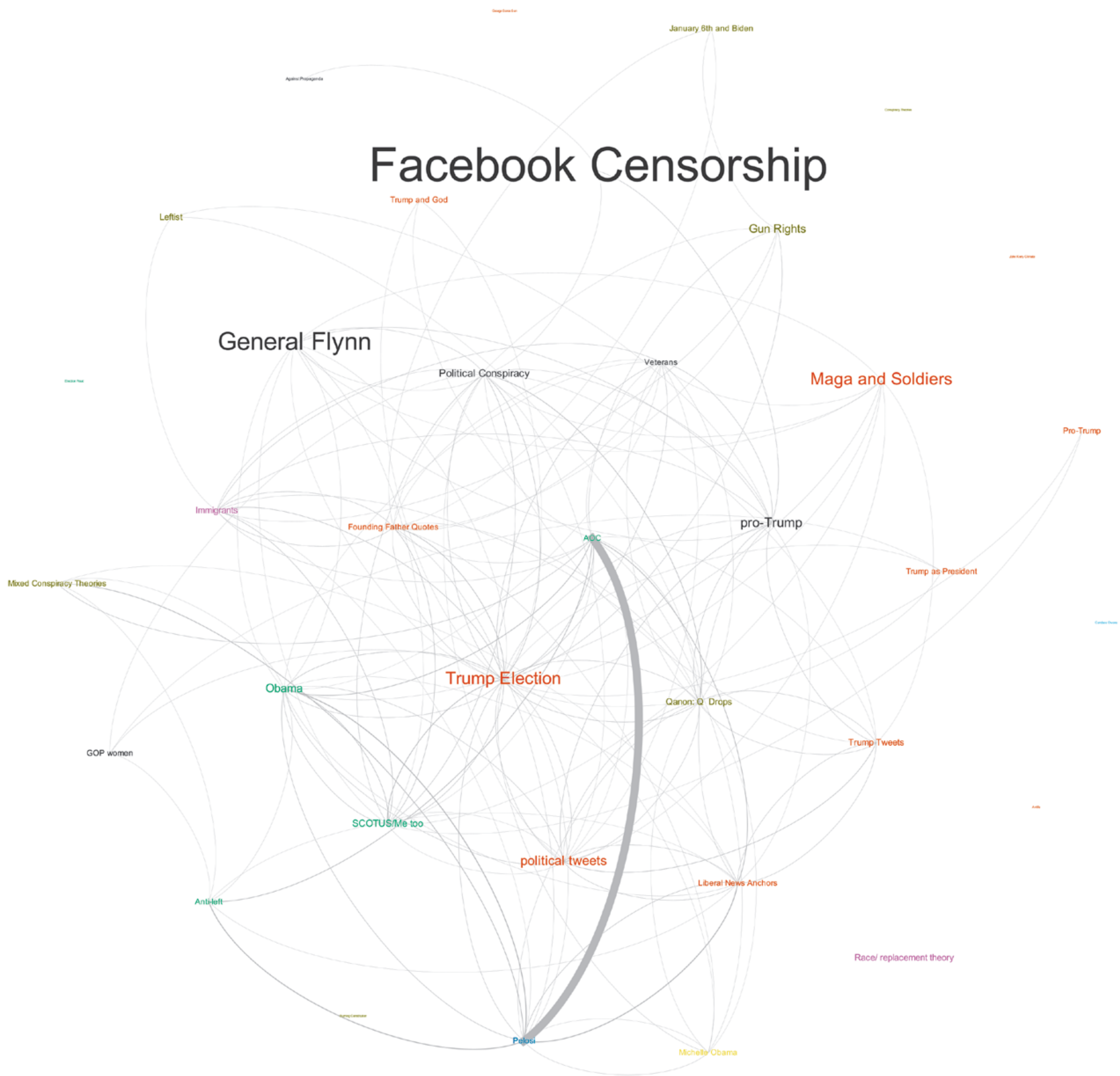

Figure 10.A: Network Graph of 1 November 2019.

Figure 10 (Panels A, B & C): Network Graphs for three time periods. The edges (the lines connecting the nodes) are the amount of user overlap between memes. In addition, the size of nodes (labels) are scaled to reflect the total amount of engagement within a meme cluster.

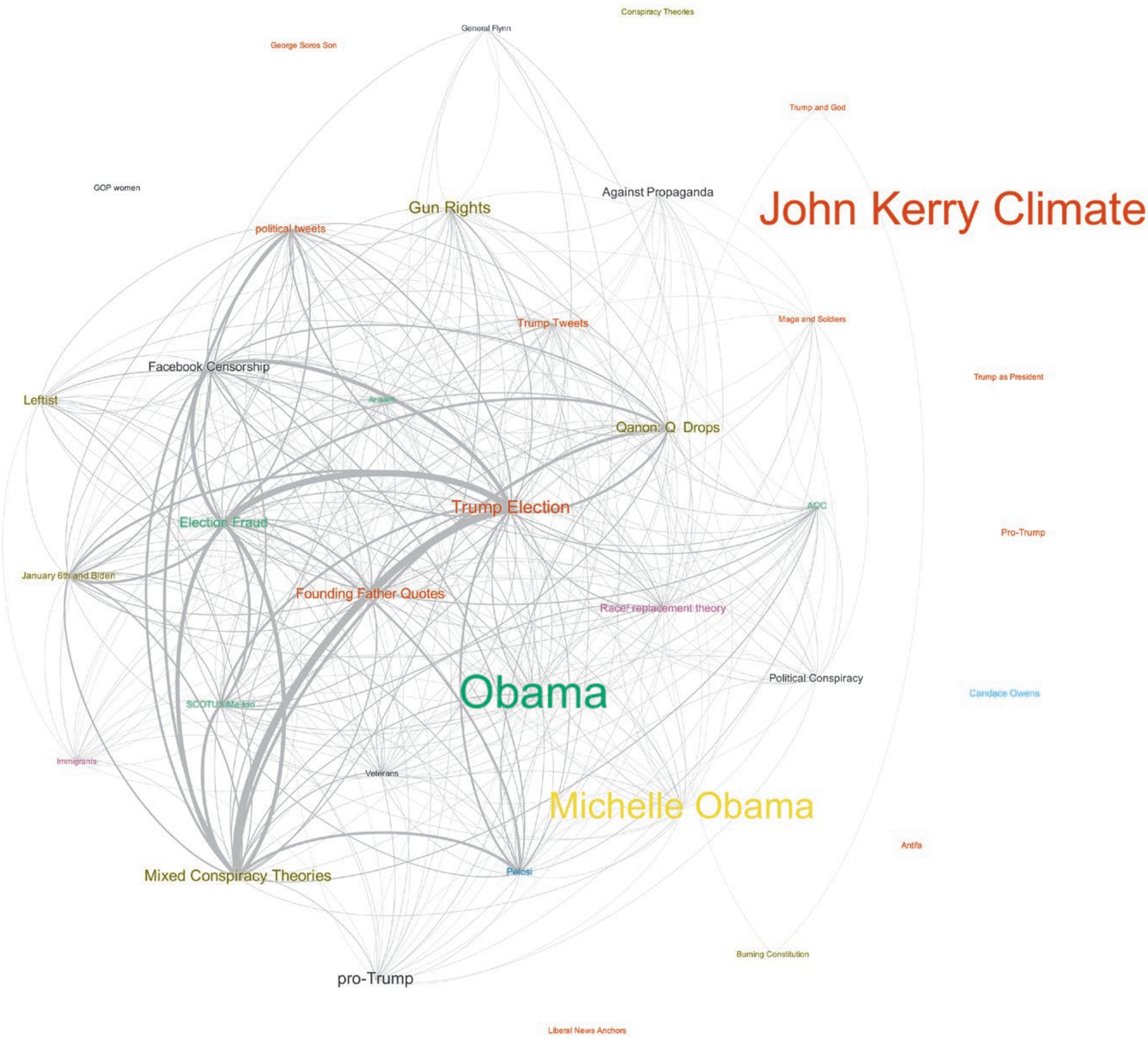

Figure 10.B: Network Graph of 3 November 2020.

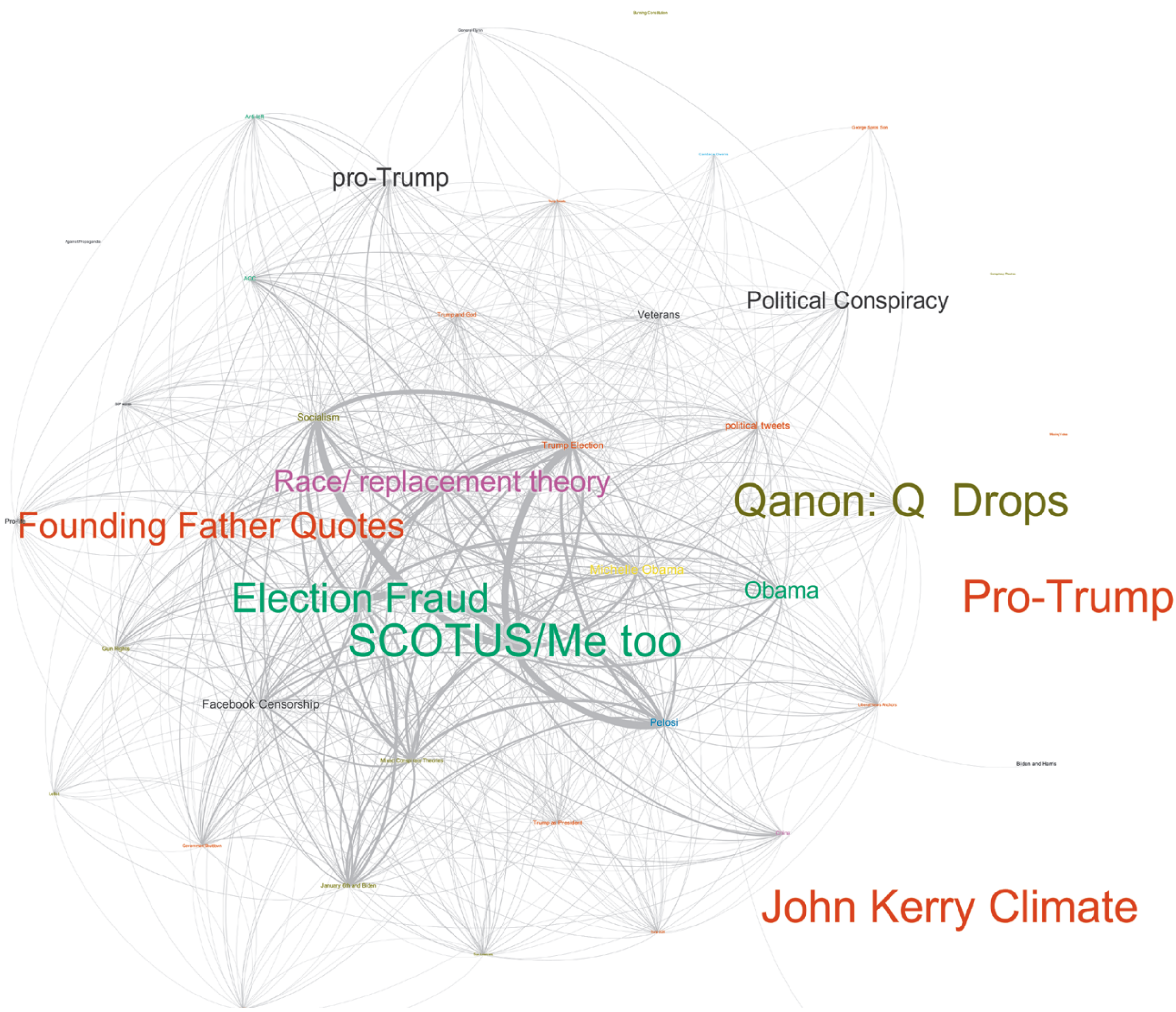

Figure 10.C: Network Graph of 6 January 2021.

Figure 11: Memes with Gendered Attacks against the Obamas. On the left, Michelle Obama is photoshopped as Time's Man of The Year. On the right, Barack Obama is photoshopped into a 'pussy hat', an icon from the Women's March on Washington, and a gendered insult in this context.

It is worth noting, however, that some of these memes were imbued with racialised and gendered meaning, particularly when leveraged against Michelle Obama (figure 11). In a site that professes to be "a home for freedom of speech", there are few repercussions – and possibly even social benefits – for attacks on marginalised groups. Accordingly, Parler users frequently leverage racialised and gendered jabs to add levity to overtly partisan topics.

Second, some memes have short but recurrent spikes in attention. As shown in figure 10.A, the graph for August 2019 prominently features the Veterans meme, which appears to spike seasonally in the autumn between Independence Day and Veterans Day. Likewise, the network graph shows that General Flynn memes followed media attention of Mueller's sentencing of Michael Flynn for misleading the FBI about his connections with a Russian ambassador, spiking in December 2018 and June 2019. Lastly, the Pro-Life category received a sharp rise in attention during the months of June 2019, when several states attempted abortion bans, and June 2020, when the supreme court removed a Louisiana abortion ban.

Finally, some memes were associated with certain topics that received steady attention regardless of the timing of their initial appearance. The most notable here are Trump Election and Political Conspiracy memes, which received a high amount of engagement even in 2019. Other topics with relative consistency of attention included Political Tweets and Founding Father Quotes. These meme ensembles share a categorical focus on partisanship (see table A.1). We found that Parler memes associated with partisanship received greater consistent engagement than those containing violence, partisanship or race. The results for the ten memes with the highest monthly median engagement are shown in figure 12. Each meme is in the partisanship category, which speaks to the consistency of partisan memes in generating high engagement throughout the period.

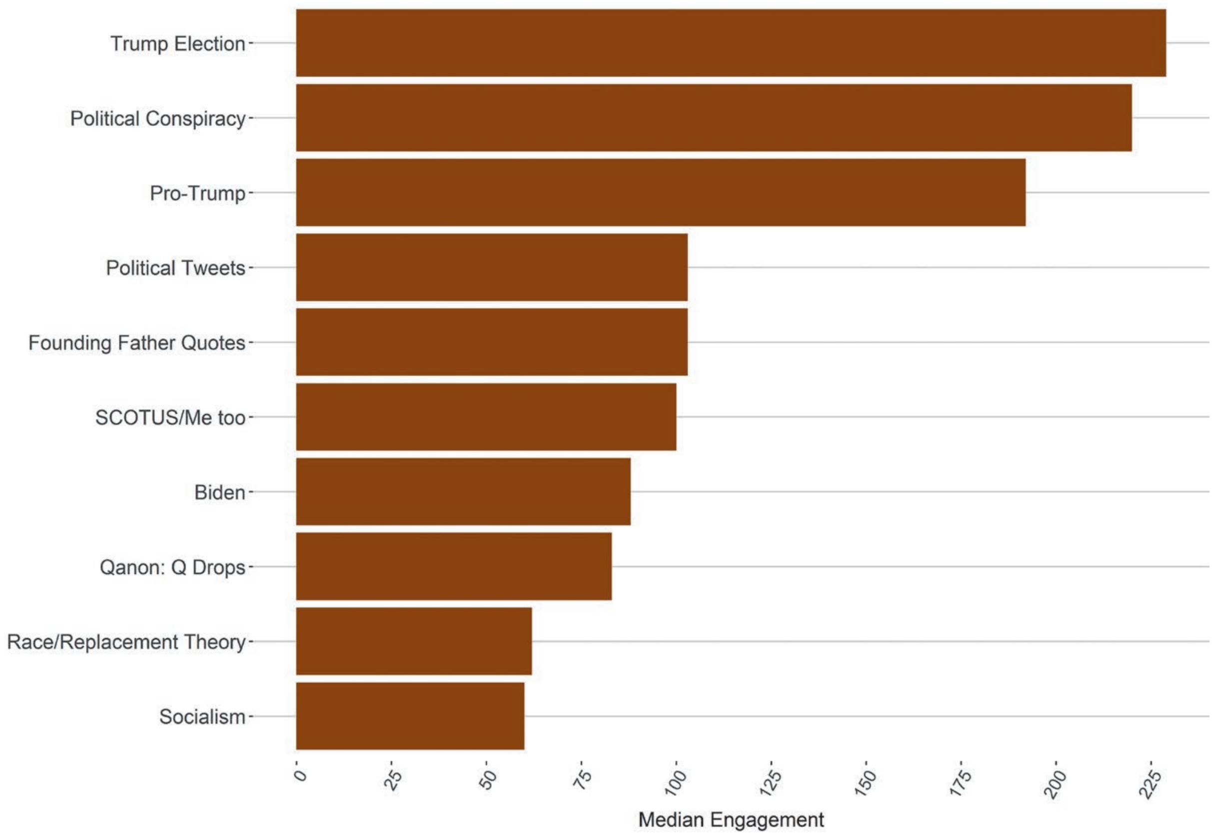

Figure 12: Top 10 Memes by Monthly Median Engagement.

Overall, these findings indicate that Parler memes sort into three categories: memes with gradual but steady attention patterns, memes with sharp attention patterns and memes with little attention change over time. Event-based memes describe the first two types of memes. As a mode of cultural discourse, memes allow online audiences to position themselves in relation to current events. The high fluctuations in the engagement of most meme topics indicate that meme topics are generally event-based and can be partly described through external patterns of influence, including seasonal events and specific news items. In comparison, memes with consistent attention tended to represent the persistent interests of site users. As a site with an apparent right-wing ideology, it is not surprising that these memes tended to focus on partisan agendas in general and Donald Trump in particular. We also saw the persistence of specific meme formats, notably founding father quotes, that represent motifs that resonate with both site users and American conservatives.

However, while the partisan interests shared by Parler's user base explains the centrality of partisanship to its meme culture, it cannot fully explain the surge in violent and racialised memes in the spring of 2020 and following the 2020 election, as noted in figure 8. To help explain this phenomenon, we examine the diffusion of memes.

Diffusion of Memes

Prior to the 2020 election, the average meme had a transmission rate of 0.065, whereas following the election, the transmission rate increased to 0.407. This translates into a 526% increase in the likelihood of transmission in the days between the election and Parler's abrupt technical problems following the 6 January insurrection (figure 13).[58]

The increase in transmission rate held true across each of the four categories we identified within the 75 clusters, though the rate of change differed across the categories. Prior to the election, gendered memes had the highest rate of transmission. However, following the election, gendered memes had the lowest increase in the rate of transmission, leading to a relatively small transmission likelihood increase of 324%. By contrast, violent memes had the lowest rate of transmission prior to the election and the highest rate of transmission following it, corresponding to a 904% increase in the likelihood of transmission. Race and partisanship had the second and third highest increase in transmission likelihood, with 550% and 506% respectively.

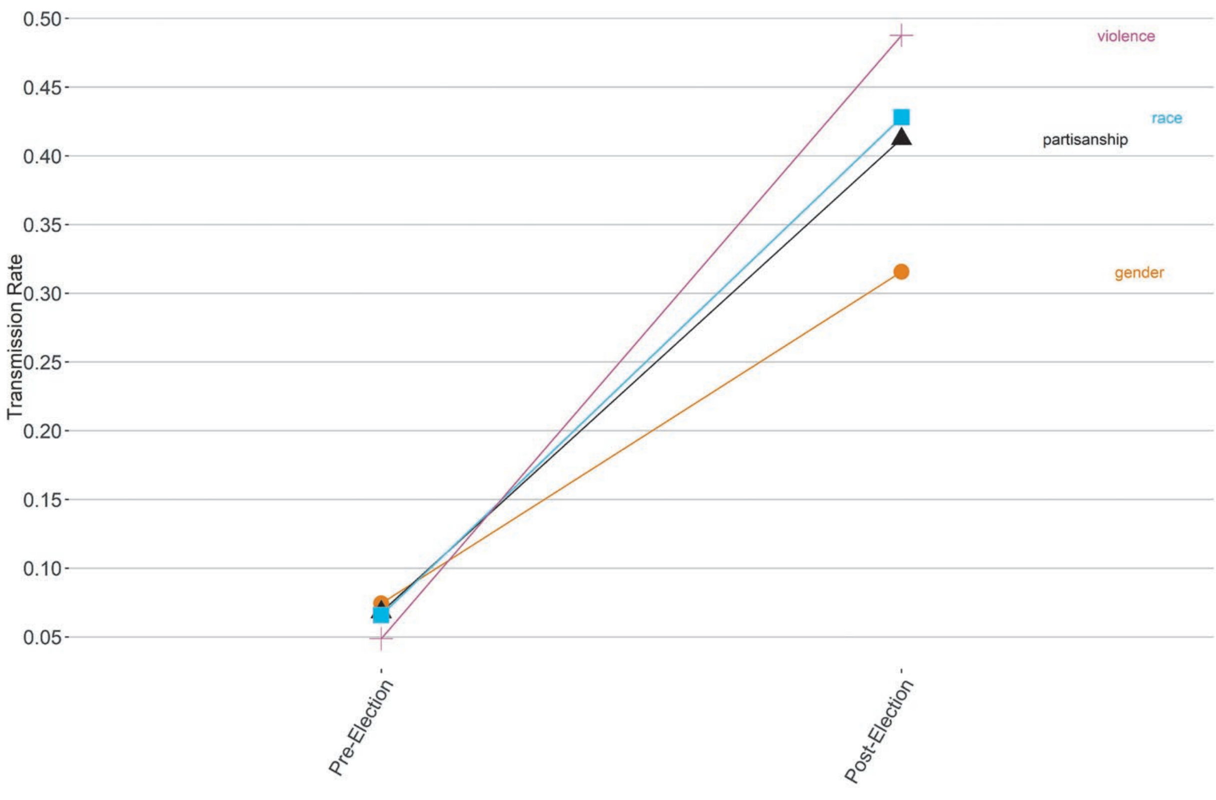

Figure 13: Meme Transition Rates Pre- and Post-Election.

58 Paczkowski and Mac, 'Amazon Is Booting Parler Off Of Its Web Hosting Service'.

These stark changes indicate that the election coincided with a significant inflection point in the posting behaviour of Parler users. First, the total increase in meme transmission rates suggests that Parler users collectively took on a more active role in sharing memes, resulting in a fivefold increase in the likelihood of sharing a meme cluster encountered in a comment thread. Moreover, the type of memes that Parler users were most likely to transmit changed. Prior to the election, violent memes had the lowest rate of transmission, perhaps due to the hesitancy of users to share memes that would be perceived as too extreme. However, the collective indignation that the site expressed following Trump's loss, stoked by the false and misleading claims of election fraud from right-wing media and figureheads, seems to have altered the social consequences of sharing violent memes. As a result, the total number of violent memes increased (figure 9) and violence became the most viral category of memes (figure 13). These results speak to the animating force of false election claims on a sympathetic social platform.

5 Conclusion and Future Work

We identified five key conclusions that shed light on the memescape of an alternative platform. First, our results indicate that no direct correlation exists between the number of memes in a topic cluster and engagement levels. The meme clusters that had the highest levels of engagement and diffusion correlated with the events on the ground, such as elections, regulations and platform censorship, and with individuals. Thus, increased production of different memes of the same topic did not equate to increased engagement. Memes with higher engagement were more present in creating and disseminating the culture.

Second, we found that memes with intersectional themes of gender and race combined with partisanship had the highest virality and diffusion. This finding is collaborated in the research related to trauma scholarship, where the risk of harm is most pronounced for scholars who are researching trauma related to their own intersection of race and gender.[59] The intersectional clusters of gender and race were also the memes that were the most violent. This provides an important insight in the backdrop of the attack on Nancy Pelosi's husband Paul Pelosi, threats during the midterm elections and supremacist conspiratorial content propagated by celebrities such as Kanye West.[60] The public discourse within the alternative platforms showcasing more violence in gender and race themes is a great concern, as content creation followed the trend of increased violence for memes with gender and race, such as Nancy Pelosi, Michelle Obama and Alexandria Ocasio-Cortez. Appeals to masculinities also included the depictions of the outgroup with feminine qualities to demonstrate presumed weakness. This finding illustrates how masculinity appeals are not only aimed at hyper, hegemonic and toxic masculinity but also specifically target women, *vis-à-vis* perceptions of what constitutes weakness or a 'lesser person'.

Third, when comparing the impact factor for each meme cluster (that is, the total number of engagements per cluster divided by the total number of images in that cluster), we found that the top five meme clusters in 2020 were Climate Change, George Soros, Pro-Trump and Michelle Obama. In comparison, clusters on MAGA and soldiers, against political lobbying, children and gender, leftists and missing votes had the highest impact in 2021. Appendix A.2 has a list of all clusters and their corresponding impact factor.

---

59 Philipp Schulz et al., 'Self-Care for Gender-Based Violence Researchers – Beyond Bubble Baths and Chocolate Pralines', *Qualitative Research* (24 April 2022), https://doi.org/10.1177/14687941221087868; Cyanne E. Loyle and Alicia Simoni, 'Researching Under Fire: Political Science and Researcher Trauma', *PS: Political Science & Politics* vol. 50, no. 01 (January 2017): 141–45, https://doi.org/10.1017/S1049096516002328; Shea Ellen Gilliam and Kate Swanson, 'A Cautionary Tale: Trauma, Ethics and Mentorship in Research in the USA', *Gender, Place & Culture* vol. 27, no. 6 (2 June 2020): 903–11, https://doi.org/10.1080/0966369X.2019.1615413.

60 For more insight into the mentioned events please read Kesa White, 'Not All Superheros Wear Capes: Identity Triggers the Trolls', *Global Network on Extremism & Terrorism (GNET)* (blog), 2 December 2022, https://gnet-research.org/2022/12/02/not-all-superheros-wear-capes-identity-triggers-the-trolls/; and Isabela Bernardo, 'Cranking Out Violence: Conspiracies Are Driving More Politically-Motivated Attacks', *Global Network on Extremism & Terrorism (GNET)* (blog), 23 November 2022, https://gnet-research.org/author/isabela-bernardo/.

Fourth, the degree of violence within memes increased, starting in mid-2020 leading to January 2021 (see figure 9 and corroborated by human coders). The transmission rate of violent memes likewise increased (see figure 13). Thus, it was possible to see violence within the public discourse increasing parallel to the events and building up towards January 2021. This illustrates the importance of identifying and monitoring trends within memes.

Lastly, the branding on memes, especially those with the high engagement, was a common thread. Memes were branded by group logos, such as Turning Point USA, Trump, QAnon and Prolife, which increased their credibility within public discourse. These meme brands can be used to track the discourse across platforms and depict thematic trends.

The findings of our research are based on only 75 clusters. For the purpose of this report, we aimed to establish and test a methodology, thus sticking to 75 clusters. In order to provide a more conclusive conclusion regarding transmission rates, we recommend pursuing multiple comparative time points and coding the whole 2,669 clusters, as well as providing a multi-platform comparison. In the future, we aim to code all the clusters and compare diffusion rates in all clusters as well as with data from other alternative platforms.

Policy Section

This policy section has been authored by Nicola Mathieson, Research Director, at the Global Network for Extremism and Technology (GNET) at the International Centre for the Study of Radicalisation (ICSR) at King's College London. This section provides policy recommendations and is produced independently from the authors of this report. Recommendations do not necessarily represent the views of the authors.

The key findings of this report carry corresponding policy implications for technology companies and policymakers. This report is the first academic work that seeks to develop a methodology for classifying meme content. Memes have become an important communication tool for partisan and extremist groups. Yet classifying images generally, and memes more specifically, poses distinct challenges for tech companies. Algorithms currently utilised by tech companies to detect extremist content are challenged by two factors. First, images are not as easy to detect as text. Second, memes are steeped in context including humour that makes it difficult for algorithms to distinguish content as extreme. This report provides a working model of meme content filtering to help platforms to identify and filter memes with extremist content.

This policy section ensures that GNET reports provide actionable research outcomes that can inform and support technology companies and policymakers to identify and prevent extremist and terrorist exploitation of digital platforms. The policy section fulfils GIFCT's core pillar of learning to improve prevention and responses to terrorist and violent extremist attacks.

1. Technology Companies

This report has identified four core areas for action for tech companies:

- This report provides a working model of meme content analysis on a single partisan platform: Parler. This model may be expanded to other platforms and other types of extremist content. Tech companies should consider providing meme data to researchers to build upon and expand this model. As demonstrated in this report, the production and dissemination of violent memes can translate into real world violence. Sharing data with researchers and extremism experts may facilitate the expansion of content classifier models targeting memes.

- The most viral memes identified in this report are those with the intersectional themes of gender and race. The intersectional clusters of gender and race were also the memes that were the most violent. This finding reflects current understandings that extremist groups often espouse racist and sexist views online. Sexism and racism are two areas that often fall into the harmful but legal category of content that poses a challenge for content moderation. This finding has practical implications for tech companies: with the vast amount of images and memes online, if tech companies are seeking to monitor extremist content, an efficient place to start is identifying memes that target the intersection of perceived out-groups.

- While images are harder than text to identify using algorithms, this report identified that the memes with the greatest engagement are often branded with group emblems or logos. By identifying extremist memes using logos rather than content and context, tech companies may be able to identify and remove the content that receives the highest engagement. Such an initiative would require a dataset of known logos and branding of extremist groups and an agreed upon designated list of extremist groups.

- A similar finding is that memes with images of people are often more extreme than text-based memes. The researchers' technology was also most effective at identifying memes of specific individuals – such as, for example, Michelle Obama – and periods when these memes were most prevalent. Drawing on this information, tech companies can best monitor and identify extremist memes by searching for specific individuals' images during important periods such as elections, political scandals and rallies.

2. Policymakers

In addition to the report findings and their implications for technology companies, this report has also identified two core areas for action by policymakers:

- The findings of this report emphasise the need for a human rights based approach to prevention. That memes that intersect race and gender are the most viral demonstrates that minority groups remain the targets of extremist violence online. We also know that minority groups are also often the target of offline extremist violence. Governments and policymakers need to develop interventions that are effective in both the online and offline space to protect targeted communities. As reductions in racism and sexism could also lead to reductions in extremism, this offers an opportunity for policymakers to implement interventions that benefit the whole of society rather than focusing on single issues.

- The report also makes clear the challenge of what is often called 'legal but harmful' content. This content remains a challenge for policymakers to legislate against, despite the known real world harm to which this content can lead. In the context of memes, violent, racist or sexist memes may fall below the threshold of violating platforms terms and conditions, as their content is distorted by coded images and humour. Governments should continue to work to develop more rigorous responses to legal but harmful content and continue to work with tech companies to develop policies in this domain.

Appendix A

Table A.1 Manual Coding of the Clusters to Themes

Cluster Labels	Themes
Orwell politics	gender
Children and Gender	gender
Pro-life	gender, partisanship
GOP women	gender, partisanship
Partisan Political Cartoons	gender, partisanship
Biden and Harris	gender, partisanship
Effeminizing Biden Voter Males	gender, partisanship
Candace Owens	gender, race
AOC	gender, race, partisanship
Election Fraud/ Anti-Biden	gender, race, partisanship
SCOTUS/ Me too	gender, race, partisanship
Kamala Harris	gender, race, partisanship
Pro-Trump/ Anti-left	gender, race, partisanship
Michelle Obama	gender, race, violence, partisanship, gender, race, partisanship
Pelosi	gender, violence, partisanship, gender, violence, partisanship
Antifa and Veterans	partisanship
Biden	partisanship
Congress	partisanship
Climate Change	partisanship
CNN	partisanship
Liberal News Anchors	partisanship
Trump as President	partisanship
Trump 2020	partisanship
Trump and God	partisanship
Trump Election	partisanship

Cluster Labels	Themes
George Soros' Son	partisanship
Pro-Trump	partisanship
Trump Tweets	partisanship
John Kerry Climate	partisanship
Missing Votes	partisanship
Biden Presidency	partisanship
Government Shutdown	partisanship
Trump still President	partisanship
Maga and Soldiers	partisanship
Founding Father Quotes	partisanship
political tweets	partisanship
Immigrants	race, partisanship
Race/ replacement theory	race, partisanship
Covid Conspiracies	race, partisanship
China	race, partisanship
Obama	race, partisanship, gender, race, partisanship
Qanon	race, violence, partisanship
End of Days	violence
Conspiracy Theories	violence, partisanship
Julian Assange	violence, partisanship
Qanon: Q Messages	violence, partisanship
Romney	violence, partisanship
January 6th	violence, partisanship
January 6th and Biden	violence, partisanship
Burning Constitution	violence, partisanship
Democratic Candidates Outlaws	violence, partisanship
Leftist	violence, partisanship
True Americans	violence, partisanship
Mixed Conspiracy Theories	violence, partisanship
Socialism	violence, partisanship
Gun Rights	violence, partisanship, race, violence

Table A.2 Impact Factors

Cluster Labels	Year	Impact Factor
John Kerry Climate	2020	157.4516129032260
George Soros Son	2020	128.92
Pro-Trump	2020	81.42033898305090
Maga and Soldiers	2021	49.83168316831680
pro-Trump	2020	33.487938596491200
Lobbying	2021	30.84
Children and Gender	2021	30.81904761904760
political tweets	2020	29.68235294117650
Michelle Obama	2020	24.0075329566855
Hollywood Immoral	2020	23.666666666666700
Leftist	2021	23.574468085106400
Missing Votes	2021	22.516129032258100
Democratic Candidates Outlaws	2021	20.946902654867300
Julian Assange	2020	18.64761904761910
Government Shutdown	2021	16.812680115273800
Biden and Harris	2021	16.485714285714300
China	2021	15.53781512605040
Pro-Trump/ Anti-left	2020	13.023809523809500
founding fathers/pandemic	2020	12.367549668874200
Gun Rights	2020	11.629555997349200
Against Propaganda	2021	11.492537313432800
Trump still President	2021	11.248430141287300
Facebook Censorship	2020	11.120833333333300
Trump Tweets	2020	10.898305084745800
SCOTUS/Me too	2020	10.389084507042300
political tweets	2020	9.740685543964230
Socialism	2020	9.683453237410070
True Americans	2021	9.043478260869570
Obama	2020	8.996630160067400
Biden Presidency	2021	8.776162790697670
Pelosi	2021	8.364356435643570

Cluster Labels	Year	Impact Factor
Pelosi	2020	8.364356435643570
Effeminizing Biden Voter Males	2021	8.24
Election Fraud/ Anti-Biden	2020	8.24
Funny Memes	2021	8.238845144356960
January 6th	2021	8.211711711711710
Covid Conspiracies	2021	8.117834394904460
Burning Constitution	2021	7.608433734939760
Race/ replacement theory	2020	7.576470588235290
Orwell politics	2020	5.90080971659919
Kamala Harris	2020	5.783681214421250
Political Conspiracy	2020	4.980392156862750
Mixed Conspiracy Theories	2021	4.831730769230770
Partisan Political Cartoons	2020	4.597468354430380
End of Days	2021	3.6666666666666700
Qanon: Q Drops	2020	3.189134808853120
Romney	2021	2.792682926829270
January 6th and Biden	2021	2.770408163265310
Conspiracy Theories in Chinese	2021	2.119047619047620

Appendix B

Appendix B provides examples of the meme clusters identified in this project. This material is graphic and offensive in nature. The Global Network on Extremism and Technology (GNET) recognises that, at times, there is a need to put primary material into the public domain but not reproduce it in a way that inadvertently propagates, disseminates or glorifies terrorism or promotes the aims of violent extremist groups.

If you would like access to Appendix B for academic purposes, please email mail@gnet-research.org.

Global Network
on Extremism & Technology

CONTACT DETAILS

For questions, queries and additional copies of this report, please contact:

ICSR
King's College London
Strand
London WC2R 2LS
United Kingdom

T. **+44 20 7848 2098**
E. **mail@gnet-research.org**

Twitter: **@GNET_research**

Like all other GNET publications, this report can be downloaded free of charge from the GNET website at www.gnet-research.org.