RESEARCH ARTICLE

MISINFORMATION

Supersharers of fake news on Twitter

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Governments may have the capacity to flood social media with fake news, but little is known about the use of flooding by ordinary voters. In this work, we identify 2107 registered US voters who account for 80% of the fake news shared on Twitter during the 2020 US presidential election by an entire panel of 664,391 voters. We found that supersharers were important members of the network, reaching a sizable 5.2% of registered voters on the platform. Supersharers had a significant overrepresentation of women, older adults, and registered Republicans. Supersharers' massive volume did not seem automated but was rather generated through manual and persistent retweeting. These findings highlight a vulnerability of social media for democracy, where a small group of people distort the political reality for many.

The pathways to news have substantially changed in the past two decades. The rise of social media as a vector for news created new challenges for democracies because large segments of society can be rapidly exposed to misinformation while others are unaware of this exposure taking place. Although prior work has examined the role of foreign influence campaigns and automated accounts (bots) in spreading misinformation on social media (*1*–*3*), relatively little work has focused on the role of ordinary citizens in propagating misinformation online. Recent work has consistently found that a small fraction of people—referred to as supersharers—account for the majority (80%) of fake news shared by registered voters on social media (*4*–*6*). Because of the rarity of supersharers, it is extremely difficult to study a meaningfully sized sample of supersharers using traditional research methods (e.g., surveys or experiments). Apart from supersharers' existence, we know little about the scale and scope of supersharers' influence online, the distinctive characteristics of supersharers, or the technical affordances that give rise to their online dominance.

Supersharers undermine a key pillar of deliberative democracy—equal representation of voices in a debate (*7*)—by flooding the digital sphere with their content. If trusted, their content may further the fragmentation of society into disjoint communities of belief. Arguably, the closest parallel to supersharing is the use of information flooding by authoritarian governments as a strategy to control and divert public opinion (*8*); yet, no prior work, to the best of our knowledge, has examined the use of flooding by voters in a democracy. To fully understand misinformation today and devise effective mitigation strategies, research must expand beyond the incidental sharers of misinformation and examine people who distort political discussion by the sheer volume of their actions.

This study leverages a panel of 664,391 registered US voters on Twitter (now X) to identify and study 2107 supersharers. We first address fundamental questions about supersharers' importance: Are they effectively "shouting" into a void where no one is listening, or are they finding large audiences online? Are supersharers vocal actors with little influence over their networks, or are they prominent actors supplying a demand for political misinformation? If supersharers are embedded in real human social networks, as suggested by prior work (*4*), they are likely to have real-world relationships with some of their followers (*9*), which places the communication in a different context of social trust. People who follow supersharers are likely to be exposed to more misinformation and potentially repeated exposure, both of which are contributing factors to belief in false claims (*10*, *11*). Over time, repeated exposure may have long-term implications, such as changing the norms of accepted behavior (*12*).

Another important piece of the puzzle is the sociodemographic characteristics of supersharers. Other than supersharers' existence, little is known about these individuals. One could predict that supersharing is conducted by young, male, and tech-savvy individuals who feel disenfranchised by mainstream society (*13*). Alternatively, supersharers may be an extension of the so-called average person, who is exposed to and shares misinformation—i.e., older, male, and right-leaning individuals (*4*–*6*). Mitigation strategies may differ depending on who the supersharers are. For example, to counter young, technologically sophisticated individuals would require a more sophisticated approach.

Finally, it is unclear how supersharers technically share so much misinformation. Prior work has suggested that supersharers are cyborgs, using automation tools to auto-tweet on behalf of the user (*4*). Research has also identified automated accounts, known as social bots, as responsible for spreading disproportionate amounts of fake political content on social media (*3*). Extensive use of automation by supersharers may indicate that they are part of a larger influence campaign, much like Russia's foreign interference in the 2016 US presidential election (*1*, *14*), China's domestic propaganda to divert public attention at critical times (*15*), and South Korea's campaign to support the incumbent president (*16*). Therefore, it is unclear to what extent automation explains the volume generated by supersharers.

This work addresses three research questions (RQs). RQ1: How important are supersharers on Twitter and in their networks? RQ2: Who are the supersharers? RQ3: What are the affordances of social media that enable supersharers to share a massive volume of fake news without facing moderation?

Method

To identify supersharers, we leveraged a large-scale panel of 664,391 registered US voters who were active on Twitter during the 2020 US presidential election (from August to November 2020). We identify supersharers (N = 2107) as the most prolific sharers of fake news that account for 80% of fake news content shared on the platform.

Similar to prior work (*4*, *6*), we rely on a source-level definition of fake news as domains that portray as legitimate news outlets but do not have the "editorial norms and processes for ensuring the accuracy and credibility of information" (*17*). We rely on the manually labeled list of fake news sites by Grinberg *et al.* (*4*), updated using NewsGuard ratings, and demonstrate the robustness of the findings to different operationalizations (see supplementary materials, section S3). To focus on political news, we restrict the analysis to tweets with external links that were identified as political by a machine learning classifier that we trained and validated against human coders. See the materials and methods for more details and additional robustness checks. Throughout, we refer to the platform as Twitter (rather than X) because our data were collected in 2020.

We address our research questions by contrasting supersharers with two main reference groups: the heaviest sharers of nonfake political news (SS-NF, N = 11,199; defined as the set of panelists that account for 80% of nonfake political news) and a similarly sized (N = 11,199)

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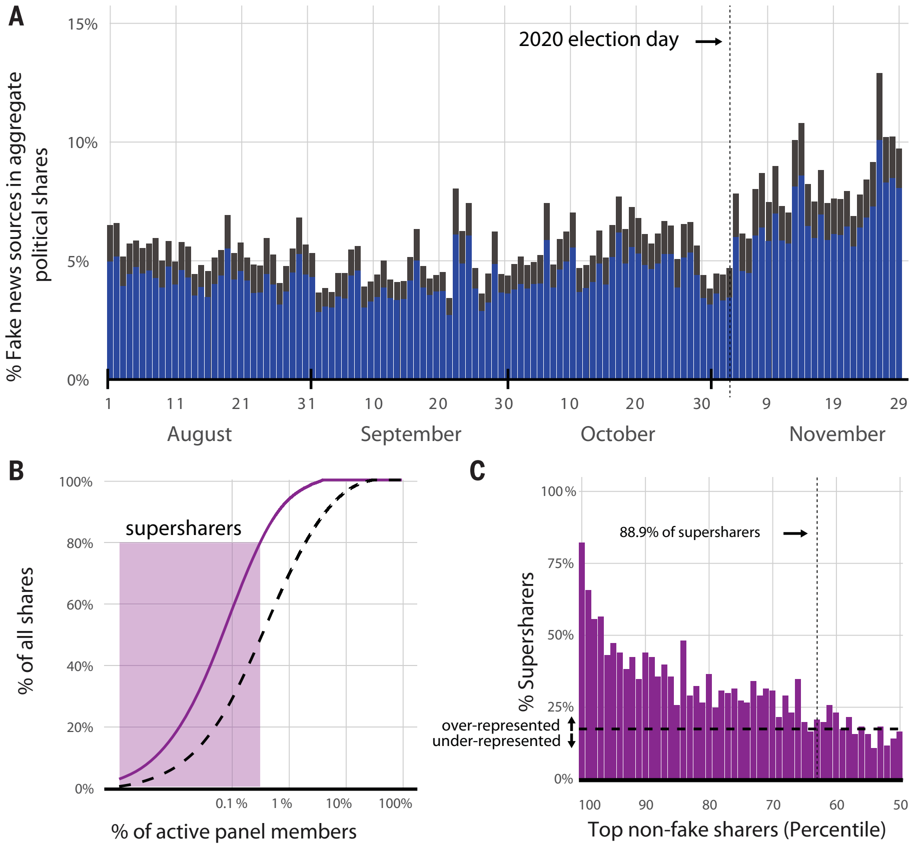

Fig. 1. Prevalence over time and concentration of fake news sharing. (**A**) Percentage of fake news sources in aggregate political shares. Blue bars show the fraction of fake news shared strictly by supersharers, and black bars show the fraction shared by the rest of the panel. (**B**) Concentration of content from fake news sources shared by panel members. The purple-shaded area highlights the volume of fake news (80%) shared by the supersharers (0.3% of the population). (**C**) Percentage of supersharers in the top percentiles of nonfake political sharers, defined as panelists accounting for 80% of nonfake political content shared. A dashed horizontal line designates the average in this subpopulation.

random sample of panelists. Some of the analyses compare a third group aiming to capture average fake news sharers, defined as users who shared three or more tweets linking to fake news sources over the study period and who are not in the supersharers group (average fake news sharers, N = 10,464).

Results

We first sought to investigate how much fake news was shared throughout the 2020 election. On an average day, 7.0% [95% confidence interval (CI): 6.7%, 7.4%] of all political news shared by the panel of 664,391 individuals linked to fake news sources. However, an extremely small fraction of our sample (0.3%; only 2107 people) accounted for 80% of the tweets linking to fake news sources. We label these individuals supersharers. Figure 1B shows the cumulative distributions of fake and nonfake news sharing by the panel. It highlights that fake news sharing (solid purple line) is considerably more concentrated in the population compared with nonfake political news sharing (dashed black line). An additional analysis showed that the level of concentration of fake news is not typical on Twitter (supplementary materials, section S8). The blue bars in Fig. 1A show that supersharers' dominance persisted throughout the election period. On a daily basis, the average supersharer posted considerably more links to political news (15.9 a day versus 5.0 for the SS-NF and 0.3 for the panel) and considerably more links to fake news sources (2.8 a day versus 0.1 for the SS-NF and 0.01 for the panel; see supplementary materials, section S1, for more details). In contrast to the 2016 election, content sharing rose after the election, mostly propelling allegations of election fraud (see supplementary materials, section S2, for more details). Figure 1C further shows that supersharers dominated nonfake political news sharing, as reflected in their overrepresentation in the top percentiles of nonfake political news sharing. These findings establish that supersharers were able to disseminate massive volumes of fake news on Twitter during the 2020 US presidential election.

To address our first research question regarding supersharers' importance (RQ1), we examined three measures of online influence. First, we examined the breadth of supersharers' reach among the 641,144 panelists for whom we have complete network information. We found that 5.2% of registered voters on Twitter directly follow a supersharer. To better understand supersharers' individual importance, we distinguish between network (topological) influence and engagement with their content. Pei *et al.* (*18*) showed that the sum of nearest neighbors' degrees is a reliable measure of network influence across different networks. Using this measure, we found that supersharers had significantly higher network influence than both the panel and the SS-NF groups ($P < 0.001$). The median supersharer ranked in the 86th percentile in the panel in terms of network influence and measured 29% higher than the median SS-NF (supplementary materials, section S11). Next, we measured engagement with supersharers' content as the fraction of panelists who replied, retweeted, or quoted supersharers' tweets relative to their number of followers in the panel. More supersharers had people engaging with their content compared with the panel ($P < 0.001$), and more panelists engaged with supersharers' content compared with all groups ($P < 0.001$; see supplementary materials, section S11, for details).

Supersharers' importance also stems from the people who follow them and the amounts of fake news that supersharers provide for them. Following the approach used in prior work (*2*, *4*, *19*), we examined the composition of content available to panelists from the accounts that they follow (see materials and methods for more details). Using this approach, we found that about a fifth of the heaviest consumers of fake news in the panel follow a supersharer. For example, 22.1% of panelists in the top decile of fake news consumption follow a supersharer (see supplementary materials, section S10, for additional thresholds). Moreover, the average follower of a supersharer was 2.5 times as likely to get political news linking to fake news sources from their network compared with the average panelist (absolute rates of 4.11% versus 1.66%). Supersharers accounted for nearly a quarter [24.4% (95% CI: 24.1%, 24.8%)] of the fake news available to their average follower and were the only source of fake news for 11.3% of their followers.

Next, we studied the distinctive sociodemographic characteristics of supersharers (RQ2). Based on logistic regression models distinguishing supersharers from each reference group separately, we found that supersharers have a significantly higher proportion of women, older adults, and Republican individuals compared with all reference populations ($P < 0.01$; full model specifications are in the supplementary materials, section S4). The gender differences stem from overrepresentation of women among Republican supersharers but not Democrat supersharers (supplementary materials, section S12). Supersharers also had a significantly higher percentage of Caucasians compared with the panel and the SS-NF groups ($P < 0.001$) but no significant difference compared with the average fake news sharers. These differences are robust to different operationalizations of fake news (supplementary materials, section S3), thresholds for considering users as supersharers (supplementary materials, section S5), presence of outliers (supplementary materials, section S6), and matched-sample specifications (supplementary materials, section S12).

Figure 2 provides descriptive statistics for the key significant differences captured by the regression models. For example, it shows that supersharers had a significantly higher percentage of women (59%) compared with all reference groups (average fake news sharer, 49%; SS-NF, 52%; and panelists, 50%), and the average supersharer is 58.2 years old, which is 5 years older than the average fake news sharer and 17 years older than the average panelist. It also shows that supersharers had the highest proportion of Republicans (64%), including the Republican-leaning group of average fake news sharers ($P < 0.001$).

Our analyses also identified significant geographic and socioeconomic differences. Supersharers were overrepresented in three US states: Florida, Arizona, and Texas ($P < 0.05$; additional contrasts are provided in the supplementary materials, section S13). The regression models distinguishing supersharers from the reference groups also identified significant differences in education attainment and annual income drawn from the US census ($P < 0.001$; supplementary materials, sections S1 and S4). Supersharers came from tracts of slightly lower educational attainment—an average of 0.3 fewer education years relative to the panel and SS-NF groups and a smaller difference relative to average fake news sharers. Relative to income expected based on education, supersharers' annual income was, on average, \$2500 US dollars (USD) higher than that of the SS-NF and average fake news sharers groups. Although these findings are robust across different model specifications, their small magnitude should be noted.

Finally, we investigated the affordances that supersharers use to produce a massive volume of content (RQ3). To thoroughly examine the potential use of automation, we used three separate approaches to identify automation and compare their results across groups. First, we used the bot detection tool Botometer (*20*) in conjunction with manual labeling to provide an upper bound for the amount of bots in our sample. We found that no more than 7.1% (95% CI: 2.0%, 12.2%) of supersharers can be considered as bots with no significant difference from the SS-NF group ($P = 0.35$), although the panel had a lower rate than both groups (1.2%; $P < 0.001$). Supplementary materials, section S6, further shows that the sociodemographic findings are robust to a small fraction of bots remaining in the sample.

Next, we examined posting times because irregular patterns can indicate the use of automation or app use (*21*). We found that supersharers are not significantly different from the reference groups in the time of day used for posting, the length or number of sessions per day, or the time between posts (see supplementary materials, section S6, for details). Moreover, we found no indication in tweets metadata that supersharers use apps that support automation more than other groups ($P = 0.75$).

The largest difference that we observed for supersharers relative to other groups is their rate of retweeting ($P < 0.001$). Three out of every four tweets (74.7%) posted by the average supersharer were retweets, which is considerably higher than the 59.9% rate found in the SS-NF group and the 32.7% rate in the panel. Our findings cannot rule out the use of more sophisticated forms of automation; however, they point to a more parsimonious explanation, where a large portion of supersharers' content is generated by manual and persistent retweeting.

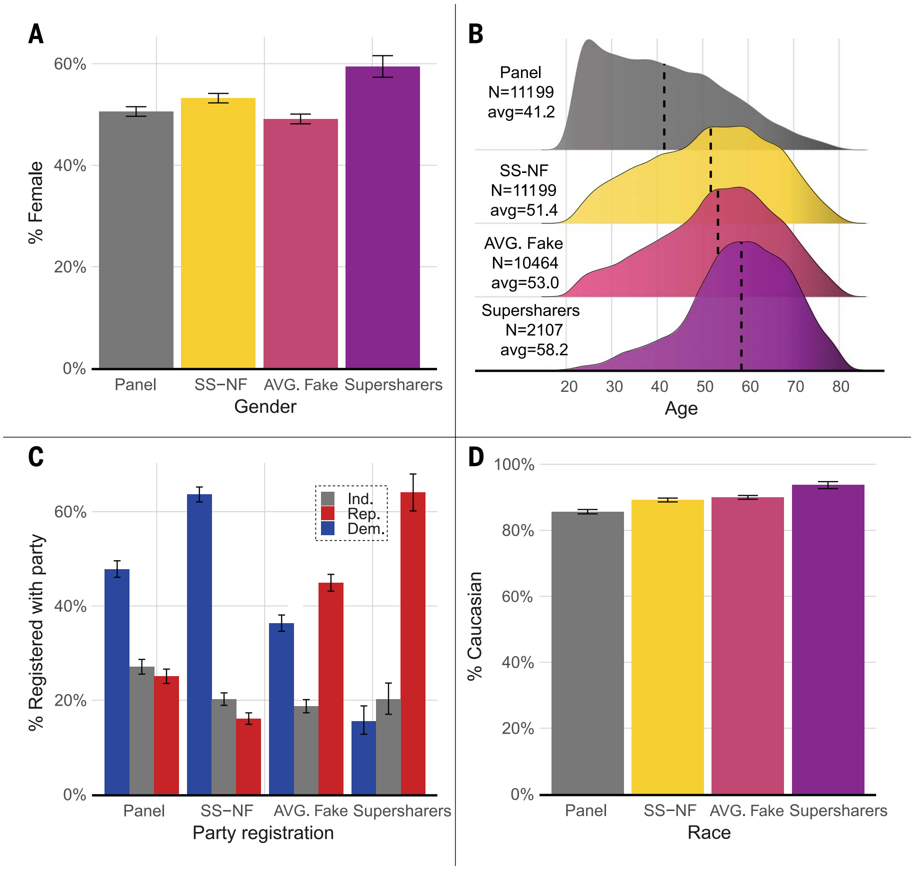

Fig. 2. Demographic differences between supersharers and three reference populations: SS-NF, average fake news sharers, and a random sample of the panel. (**A**) Gender. (**B**) Age distribution. (**C**) Party of registration. Ind, Independents; Rep, Republican; Dem, Democrat. (**D**) Race. (A), (C), and (D) show averages with 95% bootstrapped CIs. Supersharers have a significantly higher proportion of women, older adults, and Republican individuals compared with all reference populations ($P < 0.01$; full models are in supplementary materials, section S4).

Discussion

This study examined supersharers' importance, their distinctive sociodemographic characteristics, and the affordances that enabled supersharers to share massive volumes of fake news. Before this study, knowledge about supersharers (apart from their existence) was speculative.

Despite being only 0.3% of the population, supersharers reached 5.2% of registered voters in our sample and about a fifth of the heaviest consumers of fake news. To put this in perspective, it has been estimated that 3.4% of Americans on Twitter followed an account controlled by Russia's foreign influence campaign in 2016 (*2*). Another measure of scale can be based on the amount spent by the Biden and Trump campaigns on digital advertisements during the 2020 presidential election, which is estimated at $435 million USD (*22*). Roughly speaking, the candidates would have spent $20 million USD to get the same level of reach that supersharers have. Supersharers not only found a sizable audience online but were found to be influential members of their networks that provide approximately a quarter of the fake news to their followers. Across all our measures, supersharers received disproportionately more online attention.

As for sociodemographics, we found that supersharers were significantly more likely to be women, older adults, and right-leaning; were more likely to originate from Texas, Florida, and Arizona; and had small differences in education and relative income. Although some of these findings align with prior work regarding age and political leaning (*4*, *6*), the association with gender and other geographical characteristics was not previously established, to the best of our knowledge. This image is certainly distinct from the stereotype of social media manipulators as young, alt-right, and male hackers (*13*). The reasons behind this demographic composition are unclear. One reason could be higher political participation by older adults and women (*23*, *24*). Another reason may be that supersharing offers women an alternative form of activism, independent of the political establishment (*25*). Finally, it is possible that several individual differences may contribute to this behavior, such as perceived inequality (*26*), perceived threat to status (*27*), true and false news discernment ability (*28*, *29*), or even differences in sharing motivations (*30*).

In terms of technical affordances, we did not find evidence of widespread use of automation by supersharers, as suggested by prior work (*4*). Our results point to a simpler explanation: Supersharers were highly active and persistent retweeters. It is possible that the absence of automation is why many supersharers evaded Twitter's attempts to purge inauthentic behavior. This highlights the vulnerability of social media platforms to so-called low-tech social manipulation.

Practical implications

Our research shows that platform interventions that target supersharers or impose retweet limits could be highly effective at reducing a large portion of exposure to fake news on social media. Interventions that target supersharers would only affect a tiny fraction of the population and would have large benefits because of supersharers' relative importance on Twitter (supplementary materials, section S9). It is an open question whether interventions can change the motivations behind supersharers' activity and whether these could affect supersharers' local communities.

Limitations and future directions

Several limitations should be noted. First, our sample may contain systematic differences from a fully representative sample. It is unclear whether people who could be matched from voter records differ from those who could not, in particular eligible but unregistered voters. Second, the capacity to share massive amounts of content exists on other social media platforms, but the extent to which this strategy is used outside of Twitter is unknown. Third, Twitter was an important platform in American politics in 2020, but large changes in its user base (*31*)—now users of X—may affect who is supersharing.

There are also several avenues for future work to extend this research. The causal mechanisms and motivations behind supersharers' activity are not yet clear. We do not know whether supersharers' actions are a form of political activism, unintentional, or an intentional attempt to misinform others. Addressing these questions is important for advancing our understanding of supersharers and for devising more appropriate interventions. Future research should investigate supersharing on other social platforms and measure the impacts of supersharers' activity on followers' political attitudes and behaviors.

Supersharers are an extremely interesting population that requires further examination given their disproportionate negative influence on our information ecosystem. Their reach suggests that they are not part of a small and isolated community, nor do supersharers seem to function as bridges to fake news for unwitting audiences. Instead, the results cast supersharers as influential members of local communities where misinformation is prevalent. As such, supersharers may provide a window into the social dynamics in parts of society where a shared political reality is eroding. Our work is a first step to understanding these individuals, but their behavior, their motivations, and the consequences of their actions warrant further research.

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SUPPLEMENTARY MATERIALS

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Materials and Methods
Supplementary Text
Figs. S1 to S5
Tables S1 to S15
References (*33*–*44*)
MDAR Reproducibility Checklist

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