**People think that social media platforms do (but should not) amplify divisive content**

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**Abstract.** Recent studies have documented the type of content that is most likely to spread widely, or go “viral” on social media, yet little is known about people’s perceptions of what goes viral or what *should* go viral. This is critical to understand because there is widespread debate about how to improve or regulate social media algorithms. We recruited a sample of participants that is nationally representative of the US population (according to age, gender, and race/ethnicity) and surveyed them about their perceptions of social media virality (*n* = 511). In line with prior research, people believe that divisive content, moral outrage, negative content, high-arousal content, and misinformation are all likely to go viral online. However, they reported that this type of content *should* *not* go viral on social media. Instead, people reported that many forms of positive content – such as accurate content, nuanced content, and educational content – are not likely to go viral, even though they think this content *should* go viral. Importantly, these perceptions were shared among most participants, and were only weakly related to political orientation, social media usage, and demographic variables. In sum, there is broad consensus around the type of content people think social media platforms should and should not amplify, which can help inform solutions for improving social media.

**Keywords**: Algorithms, social media, virality, misinformation, polarization

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Almost five billion people – or more than half the world’s population – are now on social media (Statista, 2022a), and people use social media for about 147 minutes each day (Statista, 2022b). The content people consume on social media is greatly influenced by news feed algorithms, making social media algorithms particularly important to study. There has been intensive speculation about how social media news feed algorithms work, what type of content they amplify, and what broader impact they have on society. Indeed, some have speculated that the creation of algorithmically curated news feed on social media (as opposed to to a “chronological” news feed) had detrimental effects on democracy (Haidt, 2021). Others have argued that social media algorithms may accelerate polarization and the spread of misinformation by amplifying divisive or false content (Van Bavel et al., 2023; Van Bavel, Harris, et al., 2021; Van Bavel, Rathje, et al., 2021; van der Linden et al., 2021). However, others suggest that social media algorithms have little effect on people’s behavior as compared to user preferences (Bakshy et al., 2015), and that algorithms have many benefits for users, such as blocking out misinformation and spam (Eckles, 2022). There has been an intensive social debate about these issues among the general public and policymakers alike, along with congressional hearings about how to improve or regulate social media algorithms (C-Span, 2021).

Unfortunately, the speculation around social media algorithms likely exceeds actual public knowledge about how social media algorithms work and what their impacts are on society. Little is known about how social media algorithms work, in part due to the proprietary nature of social media algorithms, lack of transparency from social media companies, and the complexity of these algorithms (Bak-Coleman et al., 2021; Narayanan, 2023). Moreover, recommendation algorithms are frequently changing, making them exceedingly difficult to study. Because algorithms usually rely on massive, complex machine learning models, it is possible that even those who design social media recommendation algorithms know little about how they work (Eckles, 2022). Indeed, one of tech industry’s biggest open secrets is that “no one quite knows how the algorithms that govern social media actually work” (Fisher, 2022b).

Despite this lack of insider knowledge, researchers have found ways to *indirectly* study social media algorithms and the type of content they amplify. For example, research has documented what type of content tends to go “viral” (or is widely shared, viewed, or engaged with) online (Brady et al., 2017; Rathje et al., 2021). However, content might go viral because of any number of factors – such as design of social media recommendation algorithms [(Brown et al., 2022)](https://www.zotero.org/google-docs/?broken=tEwnlx), user behavior, social media platform design [(Munn, 2020)](https://www.zotero.org/google-docs/?broken=0sjoQy), or a combination of all these factors. Other researchers have more specifically examined the effect of algorithms, by, for instance, studying the type of content that is shown on algorithmically-determined versus non-algorithmically determined feeds. This has been done through, for instance, collecting social media data via browser extensions (Milli et al., 2023), or accessing internal data from social media companies (Huszár et al., 2022). Twitter has also recently made the source code from its recommendation algorithm public; however, it is unclear how much can be interpreted from this source code without more internal data from Twitter (Twitter, 2023).

In the current paper, we first review research on what tends to go viral on social media to provide insights into the type of content that is promoted on various platforms. We then recruited a representative sample of US participants to examine lay perceptions of what goes viral on social media, and compared these lay perceptions to our review of the research landscape. We also explored what people think *should* go viral on social media, and examined how this differs from what people think actually does go viral.

It is important to examine the differences in people’s perceptions of what does go viral vs. what should go viral online because some might assume that the content that users frequently engage with simply reflects what users *want* to see. Indeed, Facebook has argued that their news feed recommendation algorithms aim to amplify content that people find “valuable” and “meaningful” (Meta Transparency Center, 2023). Even if online content is divisive, the spread of divisive content online may reflect the demands and genuine preferences of social media users. People value engaging with polarizing political debates, being informed about negative events in the world, and expressing outrage about causes they care about. To use the language of economics, the type of content people engage with online might reflect their “revealed preferences,” which many economists have traditionally assumed to reflect people’s true desires (Beshears et al., 2008; Richter, 1966). Scholars have also noted that online outrage can have many upsides, such as supporting collective action and social change (Spring et. al, 2018; c.f., Brady & Crockett, 2019). Social media could also simply be accurately reflecting people’s real-world feelings and desires. For instance, Facebook has argued that discussions on social media can be “emotional and polarizing because our politics is emotional and polarizing” (Raychoudhury, 2021).

Alternatively, the type of content that goes viral on social media may reflect what is profitable for social media companies because it captures attention rather than what people or society would truly like to see (Van Bavel et al., 2023). Indeed, there are many instances in which people’s “revealed preferences” (or their behavior) do not align with their stated preferences (or what they report wanting). For example, 70% of smokers report wanting to quit smoking (Beshears et al., 2008), yet, they are often unable to quit because the product itself is addictive and tobacco companies are trying to maximize their own profits rather than the welfare of their consumers. Just as people smoke when they actually do not want to, or eat junk food when they would like to eat healthy food, people may engage with content online that they actively do not want to see.
 Social media platforms are governed by an “attention economy,” whereby algorithms amplify content that draws attention and keep users active on the platform (Simon, 1971; Williams, 2018). Divisive content is good at capturing people’s attention (Brady, Gantman & Van Bavel, 2020), and thus might be good at keeping people on social media platforms, even if people do not actually want to engage with divisive content. Supporting this perspective, research suggests that people do not like expressions of partisan animus from politicians (Costa, 2020; Frimer & Skitka, 2018) and the majority of Americans also report that they are exhausted by the news (Gottfried, 2020) and by political partisanship (Hawkins et al., 2019).

This current research helps adjudicate between these two competing perspectives by examining the potential discrepancy between what goes viral on social media, what people think goes viral on social media, and what people think should go viral on social media in an ideal world. This work has direct implications for improving social media. For instance, if most people report being unhappy with the type of content that tends to be amplified by social media platforms, news feed algorithms could be adjusted to prioritize other outcomes beyond engagement (such as accuracy or nuance). To specifically examine how people think social media could be improved, we also measured support for certain solutions, such as making social media algorithms more transparent, giving users more control over algorithms, or regulating social media algorithms. Many of these potential solutions have been discussed widely or introduced in proposed legislation, such as the “Filter Bubble Transparency Act” (Thune, 2021).

**What goes viral on social media?** A number of studies have identified certain features of content that are related to online virality (Berger & Milkman, 2012; Brady et. al, 2017, Rathje et. al, 2021; see **Table 1** for summary). Most of these studies are correlational, and examine the features of social media posts that are correlated with engagement (such as “likes” or “shares”), with engagement being measured as a continuous variable.In other words, most of these studies look at factors that increase the chances that people like or share a post. For example, several studies have found that social media posts containing moral and emotional words, such as “hate” or “blame,” tend to be shared 15-20% more in the context of online political debates, among ordinary citizens and political elites, and across several countries (Brady et al., 2017, 2019, 2021; Valenzuela et al., 2017; see also Burton et al., 2021). This may explain why people are more likely to encounter moral violations when using social media than when using any other form of media, such as television or print media (Crockett, 2017).More broadly, negative emotional content tends to receive more engagement on social media. An analysis of 22,743 A/B tests from the website Upworthy found that news stories were more likely to be clicked on when they contained negativity in the headline (C. E. Robertson, Pröllochs, et al., 2022). Other work has found that negative emotions such as anger (Fan et al., 2020) and general negative sentiment (Hansen et al., 2011; J. P. Schöne et al., 2021) spread further on Twitter than positive or neutral sentiment.
 The idea that negativity gains more traction is not unique to social media. For instance, the long-standing colloquialism “if it bleeds, it leads” has referred to the fact that negative news tends to get more attention (Pooley, 1989). Additionally, psychologists have noted that humans tend to have a domain-general negativity bias, paying attention more to negative than to positive information (Baumeister et al., 2001; Rozin & Royzman, 2001). However, while the news stories that people viewed or shared on social media tended to be negative, the news stories that were at the top of the New York Times “most emailed” list tended to be more positive (Kraft et. al, 2020). Furthermore, politicians receive more engagement on posts expressing happiness on Instagram as compared to Facebook (Bossetta, 2022), suggesting that different social media platforms may have different audiences and incentive structures that influence whether or not negativity goes viral. Negativity is also more likely to be shared among public figures as opposed to ordinary users (J. Schöne et al., 2022), further illustrating the importance of context.
 Others have suggested that content that evokes high-arousal emotions, whether these emotions are positive (e.g., awe) or negative (e.g., anger or anxiety), tends to be shared more. For example, *New York Times* articles that evoke both high-arousal positive and high-arousal negative emotions tend to be shared more (Berger & Milkman, 2012) and emotionality predicts the sharing of science articles (Milkman & Berger, 2014). However, whether high-arousal positive versus high-arousal negative emotions go viral may depend on context and culture. For instance, while high-arousal negative emotions such as anger are more “contagious” in the United States, high-arousal positive emotions such as excitement are more contagious in Japan (Hsu et al., 2021).
 Divisive or polarizing content—especially about one’s political out-group—tends to go viral, as well. For instance, posts on Facebook and Twitter from politicians and partisan news media sources received more engagement if they referred to the political out-group (Rathje et al., 2021). For instance, each individual term referring to the political out-group increased the number of shares of a social media post by 67%. This paper found that, while moral-emotional language and negative language also predicted virality, out-group language was by far the strongest predictor of virality. Posts about the political out-group received high levels of “angry” and “haha” reactions, suggesting outrage and derision. Similarly, expressions of out-party hate from politicians, while less common than expressions of in-group favoritism, received more engagement (Yu et al., 2021). Additionally, controversial news (Kim & Ihm, 2020) and expressions of “indignant disagreement” among politicians receive more online engagement (Messing & Weisel, 2017). The most politically extreme politicians also have the most followers on Twitter (Hong & Kim, 2016), perhaps because they share more divisive or controversial content.
 This online incentive structure, which promotes the creation of divisive content, may have changed how politicians used social media. Indeed, one study found that the incivility in the tweets of American politicians has risen over time (Frimer et. al, 2022), and this increase in incivility was mediated by the amount of positive feedback uncivil tweets received. In other words, politicians who received more likes and retweets for incivility were more likely to post more uncivil content afterwards. Algorithms may also play a role in the amplification of divisive content. Recent work found that people’s algorithmic (as opposed to chronological) Twitter feeds contained more posts expressing out-party animosity and anger, indicating that certain features of social media algorithms may play a role in these patterns (Milli et al., 2023). While both conservatives and liberals benefit roughly equally from expressing out-group animosity (Rathje et al., 2021), recent work suggests that conservative voices may be amplified more in general by social media (González-Bailón et al., 2022; Huszár et al., 2022), though it is unclear why this is.
 Social media also seems to amplify the spread of misinformation and conspiracy theories (C. E. Robertson, Pretus, et al., 2022; van der Linden et al., 2021). False claims (that have been fact checked) tend to be shared more than true claims (Juul & Ugander, 2021; Vosoughi et al., 2018a), leading to the possibility that some types of misinformation may achieve more virality than true news. Similarly, fact-checked COVID-19 rumors were more likely to go viral than fact-checked true COVID-19 claims, especially if these rumors contained moral-emotional language (Solovev & Pröllochs, 2022). The popularity of certain types of misinformation or conspiracy theories may be related to their novelty (Vosoughi et al., 2018a), their emotionality (Fong et al., 2021; Pröllochs et al., 2021), their expressions of moral outrage (McLoughlin et al., 2021), or their tendency to derogate the outgroup (Osmundsen et al., 2021; Robertson et al., 2022). While visits to untrustworthy sites make up only 2% of overall web traffic, they make up about 14% of Facebook engagement, suggesting that untrustworthy websites may receive more social media engagement than actual web visits (Altay et al., 2022).
 However, it should be noted that many studies only looked at true and false claims that had previously been fact checked, which may potentially bias results toward looking at instances of already viral misinformation (Altay et al., 2023). Additionally, the relationship between falsity and virality might differ across different platforms, potentially due to different platform design choices, algorithms, user bases, and social norms. For instance, a recent study found that fact-checked true claims were more likely to go viral on Reddit than fact-checked false claims, which diverges from the results of prior studies (Bond & Garretta, 2023). Recent work also suggests that people choose to engage with more false and hyperpartisan news than they are exposed to on Google search, suggesting that self-selection (as opposed to algorithmic amplification) may drive some of the engagement with misinformation (R. E. Robertson et al., 2023). The results of this study may also reflect the fact that Google search algorithms surface different types of content than social media algorithms, potentially because Google might have different incentive structures and goals than social media companies (e.g., they may be more focused on promoting relevant content as opposed to attention-grabbing content).
 It is difficult to discern universal factors that drive virality, and ***Table 1*** notes that study results often vary by culture, context, and measurement, meaning that it is difficult to discern universal drivers of virality. These could possibly explain contradictory results across studies. Future work on social media virality can take advantage of more advanced methods, such as recent advances with large-language models (Rathje et al., 2023; Ziems et al., 2023), to better measure constructs in social media text. Cross-cultural studies could also help examine how the predictors of virality vary across culture and topic. Moreover, it is not always clear how much users drive the spread of certain types of content as compared to algorithms. Indeed, these factors are often interwoven – the engagement of hyper-partisan users and political elites might be critical to trigger algorithmic amplification. As such, disentangling these factors is extremely difficult.

**Table 1**. Factors that have been found to be associated with social media virality.

| **Driver of Virality** | **Evidence**  |
| --- | --- |
| Moral-Emotional Content | * Experiencing sampling data suggested that people were more likely to encounter moral violations on social media than in person or when consuming other forms of media (Crockett, 2017).
* Each additional moral-emotional word (e.g., “hate” or “blame”) added to a social media post led to an increase in the predicted number of retweets that post received among Twitter users (Brady et. al, 2017) and politicians (Brady et. al, 2019).
* A meta-analysis of 27 studies that each additional moral-emotional word added to a post was associated with a 12% increase in engagement (Brady & Van Bavel, 2021a).
* Moral outrage, as measured by a machine learning classifier, predicted increased engagement on Twitter (Brady et. al, 2021).
* Brady et al., (2020) found in a lab study that moral and emotional words captured attention faster than neutral words, and that attentional capture in the lab predicted the virality of tweets online.
* **Context/Caveats**: These studies primarily look at online political conversations.
 |
| Negative Emotions | * An analysis of A/B tests from the news website Upworthy that negativity increased news consumption (Robertson et. al, 2022).
* Anger was associated with increased virality among weak ties on social media in China (Fan et. al, 2020).
* Negative news received more engagement on Twitter than positive or neutral news (Hansen et. al, 2011)
* Negativity spread further on Twitter after both negative and positive political situations (Schöne et al., 2021).
* **Context/Caveats**: News stories that people privately viewed or shared on social media tended to be negative, while the news stories that were at the top of the New York Times “most emailed” list tended to be more positive, illustrating the potential contextual sensitivity of this effect (Kraft et. al, 2020). Furthermore, politicians receive more engagement on posts expressing happiness on Instagram as compared to Facebook (Bossetta, 2022), illustrating that there might be differences across different social media platforms. Further, negativity was more likely to be shared among public figures than among ordinary users (J. Schöne et al., 2022).
 |
| High Arousal Emotions | * News stories expressing high-arousal emotions were more likely to be on the top of the most-emailed list of the New York Times (Berger & Milkman, 2012).
* Putting people into a state of arousal causally increased people’s willingness to share information (Berger, 2011).
* **Context/Caveats**: While high-arousal negative emotions are more “contagious” in the US (or more likely to influence the Twitter behavior of followers), high-arousal positive emotions are more contagious in Japan (Hsu et. al, 2021). Thus, the effects of high-arousal emotions on social media may depend on context and culture.
 |
| Divisive Content/Out-Group Animosity | * Each additional word about the out-group added to a post increased the predicted number of shares by 68%. Out-group language strongly predicted “angry” reactions and “haha” reactions (Rathje et. al, 2022).
* Out-party hate, while less common than in-party love, received more engagement among US politicians on social media (Yu et al., 2021).
* Controversial news received more engagement (Kim & Ihm, 2020).
* Expressions of “indignant disagreement” among politicians received more engagement on social media ([Messing & Weisel](https://www.zotero.org/google-docs/?broken=syQcVD), 2017).
* Politically-extreme politicians have more followers on Twitter (Hong & Kim, 2016).
* Incivility is rising in tweets from American politicians, and this effect is mediated by the positive feedback uncivil tweets receive (Frimer et. al, 2022).
* People’s algorithmic (as opposed to chronological) timelines contained more posts expressing out-party animosity (Milla et. al, 2023).
* **Context/Caveats:** Most of the above studies examine political elites, news sources, or other primarily political contexts instead of the postings of average users. Additionally, conservative voices may be amplified more in general more by social media platforms than liberal voices (González-Bailón et al., 2022; Huszár et al., 2022), though it is unclear why this is the case.
 |
| False Claims (That Have Been Fact-Checked) | * Fact-checked true claims spread further than fact-checked false claims (Vosoughi et al., 2018a).
* Fact-checked false claims about COVID-19 spread more than fact-checked true claims about COVID-19, especially if they contained moral-emotional language ([Solovev & Pröllochs, 2022](https://www.zotero.org/google-docs/?broken=Yu98xo)).
* **Context/Caveats:** These results depend on the sample of fact-checked claims used, and fact-checkers might be more likely to fact-check already “viral” pieces of misinformation (thus, we use the words “fact-checked false claims” as opposed to misinformation more broadly). Additionally, Altay (2022) found that low-quality news sites are visited rarely, though they receive more engagement on social media than browser visits. Further, Bond & Garretta (2023) found that fact-checked true stories received more engagement than fact-checked false stories on Reddit, illustrating that the affordances of certain social media platforms may influence false news’ propensity to go “viral.”
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*Note*. This table notes the factors that have been found to be associated with increased social media “virality” in past research. It should be noted that categories in this table are highly overlapping (for instance, moral outrage is often directed toward an outgroup, is present in misinformation, is negative, and is high-arousal).

**Why Does Some Content Go More Viral Than Others? Potential Psychological Processes**

What drives people to share and engage with negative, moral, high-arousal, divisive, and false content online, and thus make it go viral? Psychologically, this content is good at capturing our attention, and social media companies prioritize showing us content that captures our attention. Indeed, research suggests that we are faster to recognize moral and emotional words than neutral words, and this increased attentional-capture helps explain why posts expressing morality and emotion go viral (Brady et al., 2020). Negativity might also be better at capturing our attention than positivity, since it has long been noted that humans have a negativity bias, or preferentially attend to negativity more than positivity (Baumeister et al., 2001; Rozin & Royzman, 2001). A 17-country study found that exposure to negative news evokes more psychophysiological arousal than exposure to positive news (Soroka et al., 2019), which could explain why we attend to, and thus engage more, with negative content. Physiological arousal has also been found to promote sharing behavior. For instance, putting people into a state of physiological arousal led them to report higher intentions to share articles (Berger, 2011), suggesting that arousal might causally influence sharing behavior. These tendencies may be shaped by evolution – negative, high-arousal, group-based or moral content could all signal some sort of physical or social threat that we need to resolve (Petersen, 2020; Van Bavel et al., 2023).

Content that we engage with online might also be good at appealing to people’s psychological motivations – such as identity-based motivations, status-seeking motivations, and social bonding motivations (Brady et al., 2019; Petersen et al., 2021; Pretus et al., 2021). Experiments suggest that sharing moral and emotional language makes people appear to be loyal ingroup-members (Brady & Van Bavel, 2021b), so people might share this type of content to be looked upon positively by their group. People are also socially reinforced on social media (through likes and shares) (Brady et al., 2021), and may be motivated to share or engage with moral outrage in order to get social approval. Sharing content that is critical of one’s out-group may also make someone appear to be a loyal-ingroup member, and thus fulfill social belonging motivations (Brady & Van Bavel, 2021b). People may also engage in status-seeking motivations online (Peterson et al., 2020). Indeed, people tend to share content that reflects well on them (Milkman & Berger, 2014). Status-seeking motivations can explain both the sharing of positive as well as false or polarizing content. For example, one study found that people high in the trait of “status-driven risk taking” were more likely to share hostile content online (Bor & Petersen, 2022). Misinformation often contains social stimuli, such as gossip (Acerbi, 2019), as well as mentions of political out-groups (Osmundsen, 2021), indicating that misinformation might be particularly good at appealing to social or identity-based motivations. Similarly, viral true news often contains social content (Al-Rawi, 2019). It is unclear how the average person perceives these dynamics on social media. We address this issue in the next section.

**Lay perceptions of social media**

 In the first section of this paper, we reviewed what type of content goes viral on social media, finding that prior research suggests that moral-emotions, negative emotions, high-arousal emotions, divisive content, and fact-checked false claims are all associated with increased social media “virality.” Here, we examine the public’s lay perceptions of what goes viral on social media to see if it mirrors the scientific literature, and examine what people think *should* go viral on social media.We collected a sample of 511[[1]](#footnote-1) United States participants from the survey platform Prolific Academic. This sample was quota-matched to be nationally representative of the general population by age, ethnicity, and gender (n = 511, *M*age = 45.69, *SD* = 16.33, *M* = 246, *F* = 260, non-binary = 5, Democrat = 342, Republican = 169). We asked participants to rate what type of content they think goes viral versus what kind of content they think should go viral on social media in a within-subject experiment. We told people to think of the social media platform they normally use when answering these questions, and we told participants that do not use social media to make their best guess.

 Participants were asked to rate on a likert scale from 1-7 (1 = *strongly disagree* to 7 = *strongly agree*) the extent to which they thought the following types of content went “viral” on social media: content that evokes intense emotions, divisive/polarizing content, moral outrage, misinformation/conspiracy theories, content that evokes negative emotions, people criticizing their enemies, hateful content, content that evokes positive emotions, content that evokes non-intense emotions, accurate information, thoughtful/nuanced content, people praising their allies, and educational content. The first seven of these categories can be thought of as negative or harmful, and the last seven of these categories can be thought of as positive or constructive. These categories were selected based on prior research on social media virality (see***Table 1)***, as well as a crowd-sourcing process in which Twitter, TikTok, Facebook, and LinkedIn users were asked what they think does (and should) go viral[[2]](#footnote-2). Extended methods are reported in ***Supplementary Appendix S1***, and the anonymized dataset, Qualtrics files, and analysis code are available on OSF: https://osf.io/mn9cb. The full question text is reported in ***Supplementary Appendix S2***.

**There are stark differences between what people think goes viral vs. should go viral.**

We conducted paired (within-subjects) t-tests to examine the differences between what participants *think* goes viral versus what they think *should* go viral. Participants believed that content that evokes intense emotions, divisive/polarizing content, moral outrage, misinformation/conspiracy theories, content that evokes negative emotions, and content featuring people criticizing their enemies goes more “viral” online than it should (*ps* < 0.001). Effect sizes ranged from *d* = 1.76 (for hateful content) to *d* = 0.27 (for content that evokes intense emotions). In other words, people clearly believe that negative or divisive content goes much more “viral” online than it should.

 In contrast, people reported that content that evokes positive emotions, content that evokes non-intense emotions, accurate information, thoughtful and nuanced content, content featuring people praising their allies, and educational content does not go as viral as much as people think it should (*p*s < 0.001). Effect sizes ranged from *d* = 1.59 (for accurate content) to *d* = 0.73 (for content praising one’s allies). However, people believed the right amount of entertaining content goes viral on social media (*p* = 0.851). In other words, people believe that positive content goes much less “viral” online than they think it should. These differences are plotted visually in ***Figure 1***, and full paired t-test results along with effect sizes are shown in the ***Supplementary Appendix Table S1***.



**Figure 1.** There were stark differences between the content that people (n = 511) think goes viral (shown in blue) and the content people think should go viral (shown in yellow). Questions were answered on a 1-7 scale from “strongly disagree” to “strongly agree.” 4 is the exact midpoint. The p-value column represents p-values from paired (within-subjects) t-tests. There were significant differences for all categories except for entertaining content, with *Cohen’s D* effect sizes ranging from 1.76 (hateful content) to 0.27 (non-intense content) for the significant effects. Full paired t-test results and effect sizes are shown in the ***Supplementary Appendix Table S1.***

**Perceptions of social media virality are only weakly related to ideology/partisanship.**

Since many discussions about social media are politically contentious, we examined whether responses were related to political ideology and partisanship. Looking at partisan differences is important because, if Republicans and Democrats disagree on the kind of content that does (and should go viral), it may be difficult to come to consensus solutions for improving social media. This analysis allowed us to identify any potential areas of bipartisan consensus.

 We conducted all paired t-tests separately for Republicans and Democrats. Strikingly, all significant t-tests in the main dataset are significant and in the same direction when analyzed separately for Republicans or Democrats. The effect sizes for the differences between what does and should go viral are, however, descriptively larger for Democrats than Republicans. For instance, the lowest significant effect size for Republicans was *d* = 0.24 (for non-intense emotions), and the highest effect size for Republicans was *d* = 1.41 (for hateful content). The lowest significant effect size for Democrats was *d* = 0.29 (for non-intense emotions), and the highest effect size for Democrats was *d* = 2.09 (for misinformation). Yet, in general, as shown in in ***Figure 2*** and reported in ***Table S2*** and ***Table S3***, differences between Democrats and Republicans tend to be very small.

There were some small noticeable differences, however, such as Republicans reporting less concern about misinformation going viral, *r* = 0.24, 95% CI = [0.16, 0.32], *p* < .001 (see ***Supplementary Section S3*** for more details and correlations). This may reflect the fact that Republicans share more misinformation (Guess et al., 2019), polarization surrounding the definitions for terms such as misinformation, or conservatives’ greater tendency to distrust institutions (Gauchat, 2012). Despite differences like these, liberals and conservatives showed striking similarities in their stated preferences.

 We also ran a series of correlational analyses (reported in depth in ***Supplementary Section S1***, as well as ***Figures S1***-***S4***). Broadly, these analyses found that perceptions of what and should go viral were weakly and inconsistently related to age, ideology, self-reported social media usage, interest in politics, and the number of minutes people spend using social media.

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**Figure 2.** Distributions of responses for Republicans (shown in red) and Democrats (shown in blue) on each measure. As shown, Republicans and Democrats report very similar beliefs about what does and should go viral on social media.

**There is strong support for greater transparency and control over social media algorithms.**

In our nationally representative sample, we also measured support for basic solutions for improving social media content recommendation algorithms (See ***Supplementary Appendix S1*** for details). We found that 91.98% of participants answered “somewhat agree,” “agree,” or “strongly agree” to the question “social media platforms should be more transparent about how algorithms work.” We also found that 86.69% of participants agreed that users should have more control over how social media algorithms work. A majority of participants also agreed that “social media companies should not use algorithms that select what content to show users” (55.57%) and that “legislation should be passed to regulate social media algorithms” (53.42%). In sum, basic solutions such as greater transparency and control had near universal support in our representative sample. Solutions such as eliminating algorithms and regulating them through legislation were more controversial, but still supported by the majority. Since our question about regulation was ambiguously worded and people may be skeptical about the government’s ability to write effective policy about complex and rapidly changing technology, future work should explore whether people might be more supportive of some instances of regulation over others. Overall, these results suggest there are some very popular solutions to improving social media that have broad consensus.

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**Figure 3**. Democrats (shown in blue) and Republicans (shown in red) showed strong support for greater transparency and greater control over social media algorithms. Support for legislation regulating social media algorithms and support for abolishing social media algorithms altogether was more mixed.

**Discussion**

In a nationally representative survey of Americans, we investigated whether people’s perceptions of what goes “viral” on social media line up with past research and with what they think *should* go viral on social media. People believe that many forms of divisive content – such as moral outrage, intense content, people criticizing their enemies, and misinformation – all go viral online. These lay beliefs align with past research suggesting that moral outrage (Brady et al., 2021), high-arousal content (Berger & Milkman, 2012), negative content (C. E. Robertson, Pröllochs, et al., 2022), out-group animosity (Rathje et al., 2021), and misinformation (Vosoughi et al., 2018b) often go viral online. Thus, people are aware of the content that tends to be amplified in online social networks according to current research. However, the vast majority of people report that they do not think this type of divisive content *should* go viral online. Instead, they strongly believe content evoking positive emotions, accurate information, educational content, and thoughtful or nuanced content should go more viral than they currently do. This reveals a stark difference between people’s beliefs about how social media is (and how research characterizes social media) and how it should be.

These results were strikingly similar for both Republicans and Democrats, and were weakly and inconsistently correlated with other demographic characteristics. Thus, our data reveals a broad consensus in people’s belief that social media should amplify very different content than it currently does. These results question the notion that content goes viral purely because most people want that content to go viral. While some have argued for the potential upsides of moral outrage (Spring et al., 2018) and political polarization (Mac & Silverman, 2021), our results indicate that few people would be happy with social media platforms filled with outrage, misinformation, and divisive content. Social media companies, policymakers, and the general public should be aware of these gaps between how users behave on social media and users’ preferences about what social media should be like.

These results introduce a paradox: why do people engage with content online that they report not wanting to see? There are a number of possible explanations, all of which should be explored in future studies. One possible explanation is that people do not want negative content to go viral, but social media algorithms are optimized for amplifying the most attention-grabbing content, rather than optimizing for content people truly want to see amplified. This is likely shaped by economic incentives, since social media platforms’ business model depends on keeping users on their platform for as much time as possible in order to earn advertising revenue (Fisher, 2022a). Attention may not necessarily be a good measure for the type of content that people want to see. Indeed, some have noted that social media algorithms may play into our more automatic (or “system one”) preferences, as opposed to our more carefully considered (or “system two”) preferences – especially since they are trained on “mindless” behaviors, such as social media scrolling (Agan et al., 2023). Supporting this perspective, interventions that aimed to disrupt mindless social media (Allcott et al., 2022) or smartphone use (Grüning et al., 2023) led to lasting decreases in use. This has led some to conclude that a portion of social media use can be attributed to self-control failures or habit (Bayer et al., 2022) rather than intentional use.

Another possibility is that social media content is heavily influenced by a small number of users, who might not be highly representative of the general population. For instance, one report found that 10% of Twitter users produce 80% of tweets (Wojcik & Hughes, 2019). Similar work has found that a small number of Reddit users are responsible for the vast majority of toxic comments on the platform (Kumar et al., 2023), and 0.1% of Twitter users were estimated to be responsible for 80% of misinformation shares (Grinberg et al., 2019). Indeed, one estimate found that just 12 people accounted for 65% of the anti-vaccine misinformation on social media platforms during the COVID-19 pandemic (Nogara et al., 2022). Social media engagement metrics could be highly shaped by a small proportion of influential users that are highly active on social media, even if the general population do not agree with the preferences of this small portion of highly active users. People who are hostile offline tend to be hostile online (Bor & Petersen, 2022), and hostile individuals may be highly visible online and drive the spread of divisive content.

These findings have several direct implications for improving social media. For example, rather than just relying on engagement data, social media platforms should pay closer attention to self-report data (like ours) about what people *want* to see. Indeed, Facebook has tried to integrate self-report data about people’s preferences into its algorithm before. For instance, Facebook tested a feature where they downranked posts in the news algorithm that users rated as “bad for the world.” Facebook, however, decided to not implement this feature after discovering it reduced user engagement (Roose et al., 2020). Thus, even though it might be possible to improve the content people see on social media so that it aligns more with their self-reported preferences, social media platforms may be unlikely to do this if it has the prospect to reduce user engagement and undercuts the profits of social media companies. Thus, the interests of individuals and society are likely to be displaced by the economic goals of these companies.

Our results suggest that there are several highly popular solutions for improving social media from outside technology companies, through regulation and other changes. The vast majority of people in our sample supported greater transparency for social media algorithms and greater personal control over social media algorithms. One potential way to institute greater transparency is to give users the ability to change the content amplified in their own newsfeeds, and to give independent researchers access to data from social media companies so that the potential harms of social media platforms can be assessed in a non-biased manner (Persily & Tucker, 2020; Van Bavel, Harris, et al., 2021). This approach appears to have wide, bipartisan support. However, these solutions should be empirically tested, as they may come with unexpected downsides (Brady et al., 2023), such as allowing conspiracy-minded individuals to self-select into conspiratorial rabbit holes (R. E. Robertson et al., 2023)

 One limitation of this work is that it is based upon self-report survey responses, which should not always be taken at face value. It is also possible that people’s survey responses are shaped by factors such as social desirability, or a need to present oneself in a positive fashion (Edwards, 1957). Further, people’s negative perceptions of what goes viral on social media might be biased by people’s tendency to remember negative and emotional experiences (Kensinger & Corkin, 2003). People’s responses might also be shaped by algorithm aversion (Dietvorst et al., 2015), or the general tendency for people to distrust algorithms that make errors (even moreso than humans that make errors). While our self-report data come with limitations, they strongly suggest that social media behavior might not reflect the true desires of the population or average user.

 Another potential limitation of this study is that we measured whether people approved of constructs such as misinformation, hate speech, and moral outrage in the abstract, even though people might not agree on what specifically counts as hate speech or misinformation. However, research suggests that both conservatives and liberals in the US and Denmark tend to agree on what hate speech is, and believe that severe hate speech should be restricted (Rasmussen, 2022). Furthermore, laypeople are reasonably good at differentiating between low and high-quality news sources (Pennycook & Rand, 2019) and headlines (Rathje, Van Bavel, et al., 2022). Additionally, people often desire basic content moderation decisions that censor hate speech and misinformation, and do not desire unmoderated free speech online (Kozyreva et al., 2023).

Further, while our study speaks to people’s stated preferences, it has little to say about how these preferences are related to online behavior. Future research could potentially link social media data to survey data (Rathje, He, et al., 2022) to see if the same people who think negative content should not go viral also engage with negative content. Though it should be noted that people’s survey responses have been found to be correlated with online news sharing behavior (Mosleh et al., 2020), suggesting that survey responses might be reasonable proxies for offline behavior.

 Future research should also test whether a social media matching people’s self-reported ideals would actually be better in practice. As Facebook found, a social media with less content that people think is “bad for the world” may be less engaging overall (Roose et al., 2020). However, building a social media that aligns with people’s self-reported values may produce a more sustainable technology that optimizes human flourishing rather than monetizing attention at any cost.

**Conclusions**

While Facebook[[3]](#footnote-3) has argued that social media simply reflects “the good, the bad, and the ugly” (Raychoudhury, 2021), it appears that most people think – in line with social science research – that social media too often amplifies the bad and the ugly. However, people report *wanting* social media platforms and algorithms to amplify more of the good, and less of the bad and the ugly. Specifically, people across the political spectrum think social networks should amplify accurate, educational, and nuanced content as opposed to divisive, false, and negative content. Social media algorithms can be modified to amplify content that is more in line with people’s stated preferences, instead of simply prioritizing the most engaging content. Further, social media algorithms can be made more transparent and users can be given more control over social media algorithms, since the overwhelming majority of people support these solutions. While it may be challenging to change the design of social media platforms, the majority of people agree on some key points about what social media should amplify and how it should be improved. We hope our paper provides a scientific roadmap for improving social media.

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1. Our original planned sample size was 500, though we oversampled slightly to account for unfinished respondents and instances of non-response. [↑](#footnote-ref-1)
2. The following was posted on Twitter: <https://twitter.com/jayvanbavel/status/1557385190346989568?s=20&t=0lZoJyTstZK_WvZ6CJUamQ>. The following was posted on LinkedIn: [https://www.linkedin.com/feed/update/urn:li:activity:6963158807183069184?updateEntityUrn=urn%3Ali%3Afs\_feedUpdate%3A%28V2%2Curn%3Ali%3Aactivity%3A6963158807183069184%29](https://www.linkedin.com/feed/update/urn%3Ali%3Aactivity%3A6963158807183069184?updateEntityUrn=urn%3Ali%3Afs_feedUpdate%3A%28V2%2Curn%3Ali%3Aactivity%3A6963158807183069184%29). And the following was posted on TikTok: [https://www.tiktok.com/@stevepsychology/video/7132223775965236486?is\_copy\_url=1&is\_from\_webapp=v1](https://www.tiktok.com/%40stevepsychology/video/7132223775965236486?is_copy_url=1&is_from_webapp=v1). We took responses to these social media posts in account when designing our questions, in addition to considering past research on social media virality. [↑](#footnote-ref-2)
3. This argument was made in a statement responding to a Washington Post article detailing research from Rathje et. al (2021) about how out-group animosity predicts virality on Facebook and Twitter. [↑](#footnote-ref-3)