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Trends in
Cognitive Sciences

Review

The psychology of virality

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Why do some ideas spread widely, while others fail to catch on? Here, we review the psychology of information spread, or the psychology of 'virality'. Similar types of information tend to spread in many contexts, both online and offline. This is likely because similar psychological processes drive information spread across contexts. We explain how these psychological processes interact with structural features of information environments, including norms, networks, and incentive structures. Surprisingly, widely shared content is often not widely liked, a phenomenon called 'the paradox of virality'. We discuss the strengths and limitations of the information-as-virus metaphor. We also discuss future directions for the field, such as leveraging recent advances in artificial intelligence (AI) to better understand how information spreads across cultures and contexts.

Highlights

Similar types of information (e.g., negative, high-arousal, or moral information) tend to spread both online via social media and offline via gossip.

The 'information as a virus' metaphor is often used to describe the process of information spread [e.g., some types of information are more contagious than others, and 'superspreaders' contribute to most (mis)information spread]. This metaphor has pros and cons.

Similar underlying psychological processes (e.g., preferential attention to negativity, social motivations, etc.) drive the spread of information across contexts.

These psychological processes interact with structural features of information environments (e.g., norms, networks, and incentive structures).

Future work can use recent advances in artificial intelligence to explore how information spreads across different languages, cultures, and contexts.

Toward a psychology of virality

Human communication evolved in small, face-to-face social networks [1]. Throughout history, technology has profoundly changed how information is created and shared, for better and for worse. For instance, many argue that the printing press sparked the scientific revolution. At the same time, many of the bestselling books immediately after the invention of the printing press were religious extremist texts and witch-hunting manuals [2]. Similarly, social media platforms, such as Facebook, promised to 'connect the world' and 'bring people closer together'[i]. However, they also facilitate the spread of divisive content [3]. Although AI is poised to make many aspects of life easier, it also makes it easier to generate misinformation [4,5].

Yet, the extent to which technology has fundamentally altered the spread of information remains unclear. While negativity and moral outrage 'go viral' online [6–8], offline gossip is common in regular conversation [9] and often involves negativity [10,11] or discussion of moral transgressions [12]. While people are more inclined to click on negative news on the internet [13], negative news has always sold well, leading to the popular adage 'if it bleeds it leads'[ii]. These common patterns suggest that basic psychological processes lead to similar types of information going viral in most contexts, both online and offline. Despite these commonalities, modern technologies may still influence the substance, scale, and spread of information.

Here, we review the psychology of **virality** (see Glossary), or the **psychological factors** and **structural features** that shape information spread in both online and offline contexts. We synthesize the interdisciplinary literature on information spread, noting that similar features predict information spread (or 'virality') across numerous contexts. This can be partially explained by underlying psychological factors (e.g., our attraction to high-**arousal** and negative information). However, structural features (e.g., norms, networks, and incentive structures) also interact with these psychological factors to influence information spread. While previous work on information spread has been explored in distinct literatures (e.g., literatures on social media, gossip, and word-of-mouth marketing), we integrate these diverse literatures to explore key similarities and differences in how information spreads across contexts.

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Understanding the psychology of virality is important because the information that spreads widely or goes 'viral' shapes the information diet that people consume on a daily basis. The main way in which people access news today is via social media [14], meaning that the primary way in which people access news is by consuming 'viral' content that is widely shared or amplified by algorithms. Similarly, in the offline world, people learn about 'viral' information that spreads via their in-person networks. The information that people consume online and offline can have important consequences for how they vote, feel, and behave [15,16].

We use the term 'the psychology of virality' to acknowledge the ubiquity of the virus metaphor in describing information spread. This metaphor has been widely used by academics, popular science writers, and the general public [17,18]. For example, the term 'infodemic' rose to prominence during the 2020 pandemic as a way to describe viral misinformation [19]. Beyond mere metaphor, researchers have also used epidemiological models to model information spread, suggesting that, in some ways, information does spread like a virus [20–22]. Despite its popularity and utility, this metaphor (similar to all metaphors) is imperfect and fails to capture some nuances of information spread. Box 1 provides a discussion of the strengths and limitations of this metaphor.

What goes viral on social media?

The wealth of text data on the internet launched the field of computational social science [23], which led to numerous large computational studies using 'big data' from the internet. Many of these studies focused on the study of information **diffusion** (or 'virality') [24], exploring how certain properties of information (e.g., emotional language) relate to measures of engagement (e.g., social media shares). These studies typically do not aim to predict extreme virality (as the term 'go viral' may suggest), likely because viral outliers are rare and, thus, difficult to forecast. Instead, they tend to focus on factors that are correlated with engagement.

Studies on the spread of information on social media have focused on a variety of different psychological constructs. For instance, research has found that the following variables predict information spread on social media: outgroup animosity [6,25–28], incivility [29], negativity [13,27,30,31], moral outrage [7,8,32], anger [33], misinformation [34,35], indignant disagreement[iii], and high-arousal information [36,37]. However, it is likely that several of these psychological constructs overlap. For example, moral outrage is negative, high-arousal, hostile, frequently about out-groups, and correlates with misinformation [32]. Thus, rather than focusing on several separate constructs, a more parsimonious framework is needed to organize the literature on social information spread.

The **circumplex model of affect** can help us understand the literature on information spread on social media [38]. The circumplex model is a psychological theory that suggests that all emotions can be represented as points along two dimensions of affect: **valence** and **arousal**. For instance, anger is a high-arousal (or intense) negative emotion, sadness is a low-arousal negative emotion, excitement is a high-arousal positive emotion, and calm is a low-arousal positive emotion. This model is popular in the emotion literature (although there are many alternate models [39]) and is considered by many to be better than focusing on 'basic' emotions, which vary widely across cultures [40]. In Figure 1, we map several of the key findings from the literature of social media virality on the dimensions of the emotion circumplex [7,8,13,25–37,41–48].

There is a clear pattern in the literature on virality (Figure 1). Most studies suggest that high-arousal negative emotional expressions (e.g., hostility, moral outrage, out-group animosity, and indignant disagreement) go 'viral'. There are no studies (to our knowledge) demonstrating that

Glossary

Arousal: intensity of an emotion, regardless of its negativity or positivity. Anger and excitement are both high-arousal emotions, and sadness and calm are low-arousal emotions.
Circumplex model of affect: model that proposes that emotions can be visualized according to two core dimensions of affect: valence (the negativity or positivity of an emotion) and arousal (the intensity of an emotion).
Dictionary methods: way of classifying or analyzing text data by using predefined dictionaries (e.g., counting the number of negative words in a social media post using a predefined 'negativity' dictionary).
Diffusion: another common term for information spread.
Echo chambers: environments in which individuals are primarily exposed to information that reinforces their existing beliefs, while rarely encountering opposing viewpoints. Echo chambers can occur both online (e.g., on social media) and offline (e.g., in ideologically segregated neighborhoods).
Memes: units of cultural transmission, such as ideas, behaviors, or styles, that are spread from person to person.
Paradox of virality: term used to refer to the idea that widely shared content is often not widely liked.
Psychological factors: psychological processes that may shape the spread of information (e.g., our preferential attention toward negative and high-arousal information).
Shared reality: based on shared reality theory; refers to a perceived commonality of inner states with others.
Structural features: aspects of an environment (e.g., networks, norms, or algorithms) that may influence information spread.
Superspreaders: individuals, influencers, or social media accounts that have a disproportionate role in spreading certain types of information.
Valence: positivity or negativity of an emotion. Sadness and anger are negatively valenced emotions.
Virality: information spread in online and offline contexts.

Box 1. A viral metaphor

While phrases such as 'going viral' have become popular in the digital era, the spread of ideas was described as a virus long before the arrival of the internet. During the 1970s, Richard Dawkins famously likened the spread of **memes** (or units of cultural transmission, such as ideas, behaviors, or styles) to the spread of viruses [106]. There are many ways in which information spreads like a virus online and offline. For example: (i) just as some viruses are more contagious than others, some forms of information spread more easily than others [24]. (ii) Just as diseases have symptoms, information exposure has symptoms, or psychological and behavioral consequences [107]. (iii) Just as viruses can mutate over time, and some mutations of a virus may become more (or less) contagious, information also mutates over time, with some mutations making the information more (or less) contagious [65]. (iv) Just as superspreaders disproportionately contribute to epidemic spread, superspreaders also disproportionately contribute to the spread of certain types of information (e.g., misinformation on social media) [81]. (v) Just as a crowded room is conducive to the spread of a virus, some environments (e.g., some social media platforms) might also be conducive to the spread of certain types of information [24]. Finally, (vi) just as interventions (masks, vaccines, etc.) are used to stem the spread of disease, interventions can also be used to create immunity against misleading or harmful information [108].

However, some scholars argue that this metaphor is misleading. For example, unlike viruses, information often spreads purposefully [109], spreads faster within (but not across) identity groups [110], and spreads through less connected individuals [111]. Others argue that the virus metaphor ignores human agency, since people do not passively consume information, but interpret, transform, or ignore it [112]. While this may be thought of as a weakness of the metaphor, others suggest that our tendency to ignore and resist information is a feature of our 'mental immune systems', expanding on the metaphor further [113]. Thus, there are pros and cons to this metaphor. Given that metaphors shape how we think [114], they can be useful for theorizing and generating new hypotheses, but they also risk misleading us. Rather than endorsing or rejecting the metaphor of 'virality', we acknowledge its significant influence in academic and popular discourse. Since the metaphor itself is 'viral', it is difficult to ignore in discussions of information spread.

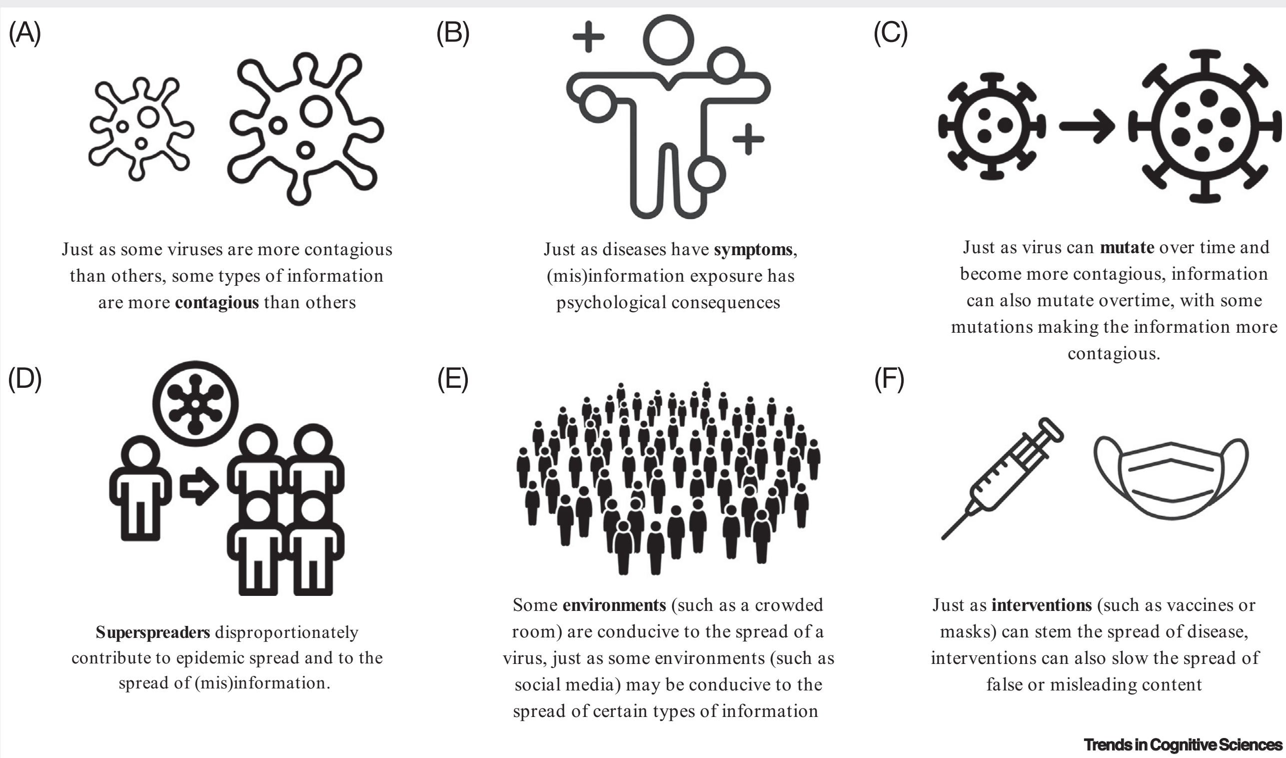

Figure I. Expanding on the virus metaphor. The metaphor of information as a virus can be used for understanding the psychology of information spread (or 'virality'). Similar to viruses, (A) some types of information are more 'contagious' than others, (B) (mis)information has 'symptoms', or psychological consequences, (C) information can mutate over time, (D) 'superspreaders' disproportionately contribute to (mis)information spread, (E) some environments are more conducive to the spread of certain types of information than others, and (F) interventions can be used to stem the spread of harmful information.

low-arousal positive content is most likely to spread. Thus, there appears to be some consistency across studies in terms of what goes viral, which can be attributed to similar psychological processes driving information spread across numerous contexts.

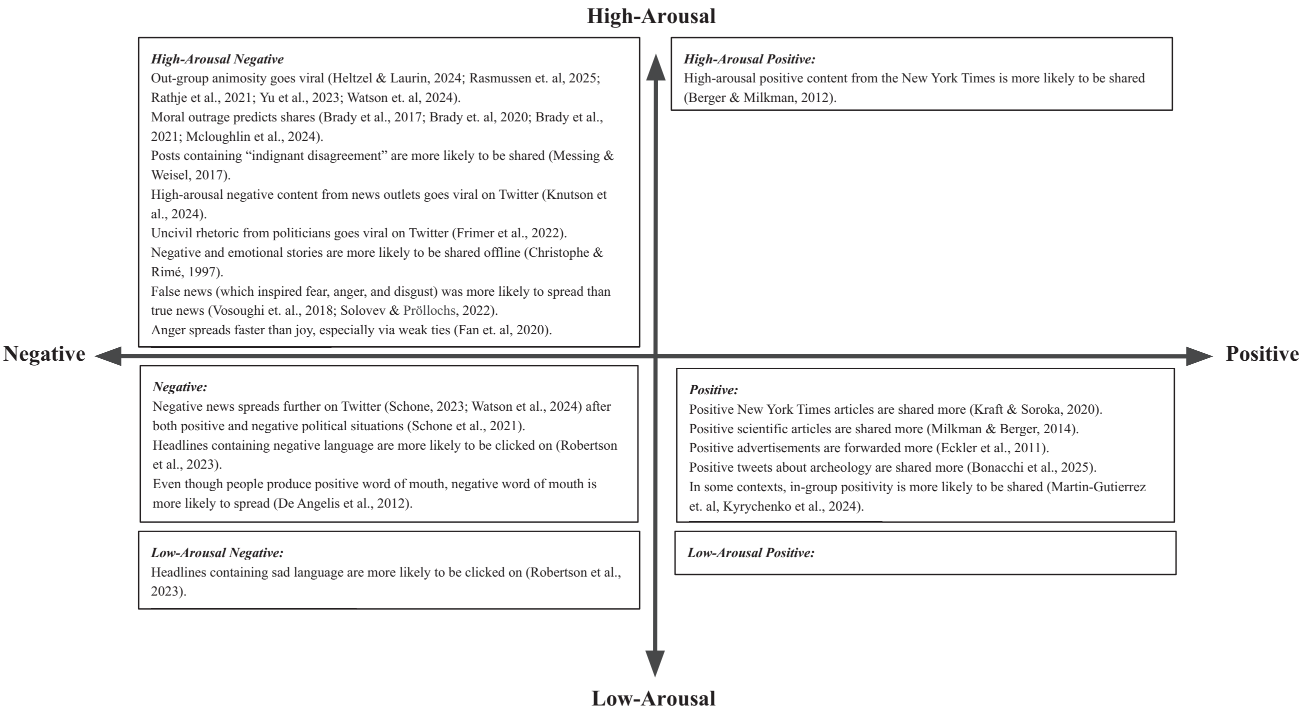

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Figure 1. High-arousal and negative content goes viral. We mapped the key studies cited in this article [see 6–8,13,25–37,41–49[iii]] according to the emotional circumplex, which represents various emotions according to two dimensions: arousal and valence. As shown, most studies find that high-arousal negative emotions are more likely to spread or go viral. However, there are several exceptions, with a few studies finding that positivity or low-arousal negativity are likely to spread in some contexts. Notably, we found no studies finding that low-arousal positive information is most likely to spread. This organization of key studies in the virality literature illustrates some striking patterns in the type of information that is most likely to spread across contexts, likely due to common psychological processes driving information spread. Note that this figure only shows a subset of key studies in the literature cited throughout this article, rather than showing a comprehensive review of all studies on information spread.

However, there are a few exceptions to this pattern. For instance, studies have found that positive *New York Times* articles [44], advertisements [45], science findings [49], and tweets about archeology [46] are more likely to be shared online. Notably, these studies look at nonpolitical contexts, suggesting that important moderators are at play (e.g., whether a message is about politics). Other work has found that negativity [31] and toxicity [50] achieve more virality among public figures than among regular users, further demonstrating the role of contextual moderators. Many of these conflicting findings can be explained by structural features of environments in which information is shared (including norms, networks, algorithms, incentive structures, etc.). We aim to reconcile these conflicting findings and explain how psychological processes and structural features interact to shape information spread.

Psychological processes underlying virality

In a crowded information environment in which many different pieces of information are competing for our attention (such as a social media news feed), one would expect that the most attention-grabbing information would be the most likely to be shared. Similarly, in the offline world, one would expect the most memorable pieces of information to be spontaneously brought up during in-person conversations. Indeed, research suggests that negative and high-arousal content is not only more likely to be shared, but is also more likely to be attended to and remembered [51,52], which may help explain the viral spread of this type of content online and offline [41].

Our attraction to high-arousal negative information likely has deep evolutionary origins [53]. It is adaptive for people to pay attention to threatening information, since it is likely to hurt our chances of survival [54]. Social media algorithms appear to take advantage of our attraction to threat to capture our attention and keep us engaged [55]. However, our evolutionary attraction to threat appears to be mismatched with the affordances of the online world [56] because it is not useful to be constantly made aware of distant threats that are constantly happening all over the globe.

Beyond attention, other psychological processes, such as motivation [57], also drive the spread of information [58]. Researchers have explored how various motivations, such as identity-based motivations [59], status motivations [60], reputational motivations [61], affiliation-based motivations [62], certainty motivations [63], and even a motivation to create chaos [64], all predict the sharing of certain types of (mis)information. Similarly, classic social psychological work from the 1940s (long before social media) suggested that status-based and uncertainty-reduction motivations drive the spread of offline rumors [65].

Sharing is a fundamentally social activity, and what people share online will likely reflect social and reputational motives. Indeed, neuroscience studies found that brain areas implicated in social processing are activated in response to viral content [66,67]. There is also evidence that more positive content is more likely to be shared than privately viewed, perhaps due, in part, to self-conscious self-presentation motives to present oneself in a positive light [44]. Furthermore, people attend to a more politically diverse set of information than they share, suggesting that social identity motives constrain the set of information that people are likely to share [68].

People's social motivations may at times conflict with accuracy motivations and lead to the sharing of misinformation [59]. For instance, making social motivations (such as our motivation to conform with our in-group) salient by making people think about whether a news story would be liked by members of their political party decreased people's ability to correctly discern the accuracy of that headline [69]. By contrast, interventions that make accuracy motivations salient lead people to share more accurate information [69–72].

A final reason people share information may be that sharing intrinsically feels good, potentially as an evolutionary byproduct of our need to communicate important information to others. Neuroscience research indicates that people find sharing information to be rewarding [73]. This desire to share may stem, in part, from our need to feel a sense of **shared reality** (or perceived commonality of inner states) with other people [74]. One perspective suggests that people's personal need to disclose negative information turns people into 'news broadcasters' whose stories inform the community of important events [75].

The paradox of virality

The modern spread of information is mediated by algorithms that show people content that they are likely to engage with. Facebook has argued that their news feed-ranking algorithm shows people what they 'want to see'[iv]. Does the fact that people are more likely to engage with high-arousal negative content imply that they like this type of content? No; several studies suggest that people report strongly disliking this content. One study found that, even though people are aware that negative and high-arousal content goes 'viral' on social media, most people across the political spectrum reported that they do not want this to be the case. Instead, they would prefer that more positive, nuanced, and accurate content goes viral [24] (Figure 2). Other studies have illustrated similar findings: for instance, most people do not approve of divisive tweets [28] or uncivil politicians from any side of the political spectrum [76].

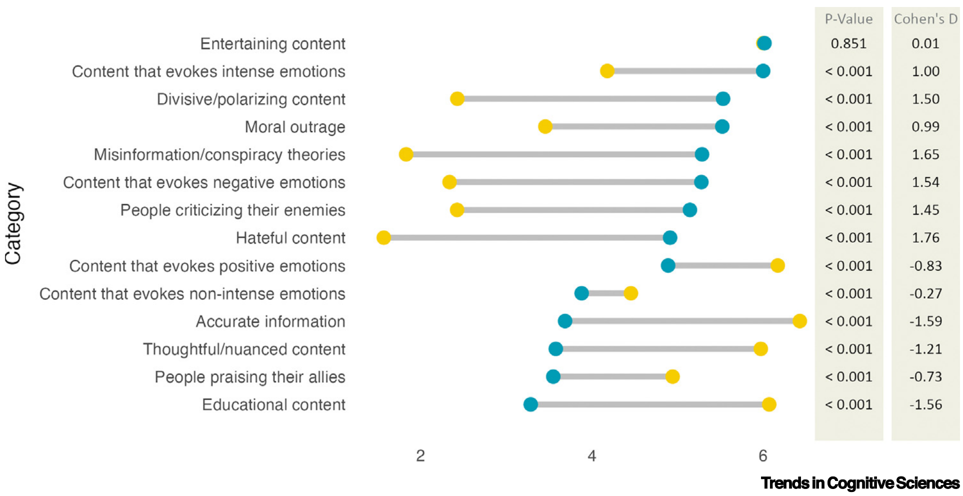

Figure 2. People know divisive content goes viral, but do not want it to. This figure shows the results of a survey of a representative sample of 511 Americans. Participants answered questions about categories of content they think do (vs should) go viral on a scale of 1 'strongly disagree' to 7 'strongly agree'. Even though participants thought that various forms of high-arousal negative content spread widely on social media, they did not want this to be the case. Instead, they thought that positive, accurate, and nuanced content should spread on social media. This is called the 'paradox of virality', or the idea that widely shared content is often not widely liked. Adapted from [24].

This gap between people's stated preferences and behavior is called the **paradox of virality**, or the idea that widely shared content is not necessarily widely liked[v]. This gap constitutes a paradox because it appears to be contradictory that people would contribute to the spread of information they do not think should spread widely. There are a few potential explanations for this paradox, which we describe below.

A revealed preference for division?

One explanation might be that people are either unaware of, or unwilling to report, their actual preferences. In other words, people's social media behavior may reflect their revealed (as opposed to stated) preferences [77]. Many economists have suggested that people's 'revealed' preferences are more meaningful than their stated preferences [78]. Indeed, in designing the news feed-ranking algorithm, social media platforms such as Facebook appear to prioritize people's revealed preferences or behavior rather than their stated preferences.

Yet, people's stated preferences are worth listening to. For instance, 70% of smokers say that they would like to quit smoking [77]. The reason many smokers continue to smoke is because of addiction, not a 'revealed preference' for smoking. Similarly, experiments have suggested that a substantial portion of social media usage can be attributed to self-control failures (akin to 'addiction') [79]. In the context of addictive products (such as social media, junk food, or cigarettes), it is important to pay attention to stated preferences, since people may not have the ability to align their behavior with their true preferences.

Social media companies can prioritize people's stated preferences to design better algorithms [55]. One series of large-scale field experiments found that unfollowing hyperpartisan influencers reduced out-party animosity and made people feel better about their social media feeds, without reducing social media engagement [80]. This suggests that aligning people's social media feeds with their stated preferences has positive consequences.

Incentive structures

Another potential explanation for the paradox of virality is that the incentive structure of many social media platforms encourages people to share information that they do not like to see. People may share content for social approval [8]. They may also dwell on content because they feel they cannot look away, just as people might feel like they cannot look away from a car crash on the side of the road. Since social media algorithms amplify attention-grabbing content, content that people cannot look away from (but do not like) may be more likely to go 'viral' on social media.

Superspreaders

A third potential explanation for why widely shared content is not widely liked is that a small number of passionate '**superspreaders**' may be disproportionately responsible for sharing it. One estimate suggests that ~0.1% of Twitter/X users share ~80% of misinformation on the platform [81,82]. A similar study found that ~3% of toxic Reddit users share ~33% of content on the platform [83]. While most people disapprove of divisive tweets, the small fraction of people who frequently interact with politicians on Twitter/X (and, thus, share most political posts) approve of divisive posts [28].

Therefore, the preferences of these 'superspreaders' who frequently share social media content may be very different from those of most people. Indeed, a survey of online participants found that most people prefer to share information that is positive about their in-party than negative about their out-party [84], despite out-party negativity going viral [6,25–28]. One reason for this discrepancy between survey results and social media data may be that a small number of people are contributing to the majority of online sharing behavior [85].

Further illustrating this 'superspreader' phenomenon, one study found that hostile tweets received more 'likes' but a lower 'likes-per-retweet' ratio [29]. This lower likes-per-retweet ratio suggests that hostile tweets were relatively less liked when accounting for how much they were retweeted and seen. A lower likes-per-retweet ratio was correlated with greater disapproval of the tweet from human judges, indicating that it is a proxy of audience approval. Thus, a high 'likes' count may give the false impression that a tweet is widely liked, when in reality, only a small fraction of those who see it like it.

Structural features shaping information spread

Is social media and the internet unique in its tendency to amplify high-arousal negative content, or does this content also go 'viral' in the offline world? Research has found that negative [42], emotionally arousing [75], and moral gossip [12] is likely to spread widely in the offline world. Positive gossip is exceedingly rare [10]. Furthermore, the word-of-mouth marketing literature suggests that, even though people are more likely to produce positive word-of-mouth marketing, negative word-of-mouth marketing is more likely to spread [43]. This observation that people produce positivity but share negativity is also found in the online world: multiple studies suggest that politicians talk about the in-group more, even though outgroup animosity spreads more [6,25]. In addition, while the average social media post is surprisingly positive [86], negativity is more likely to spread [30,31]. Overall, these studies reveal that there are striking similarities in the type of information that spreads online and offline.

Studying how information spreads offline or how information has spread historically (Box 2) can help us uncover the structural features that shape information spread. Returning to the information as a virus metaphor, psychological factors, such as the negativity or arousal of information, can make information more contagious. However, just as diseases are more likely to spread in

Box 2. The historical spread of information

Did high-arousal negativity go 'viral' long before the creation of social media and the internet? If so, it would suggest something about human psychology rather than the online world *per se*. Indeed, historical accounts appear to suggest that high-arousal negativity always went 'viral'. For instance, the phrase 'if it bleeds, it leads' is believed to have been first used during the 1980s to describe the practice of leading with negative news to attract attention[i]. The term 'yellow journalism' was used during the 1800s to refer to the practice of creating sensationalistic stories to attract attention [115].

Historical psychology can help us explore this question empirically [116]. Recent papers analyzed historical data (e.g., digitized books and headlines) to examine changes over time. Similar methodology could be used to see whether high-arousal negative language has increased over time, potentially in response to the incentive structure of modern technology.

Some articles have used these methods to explore how the spread or prevalence of content has changed throughout history. For instance, one paper found that news headlines expressed increasing levels of high-arousal negative emotions (specifically, anger, fear, disgust, and sadness) over the period 2000–2019, which coincides with the rise of social media [117]. Similarly, another study found that politicians have been using more uncivil language on Twitter/X since 2009, and this increase in incivility was found to be partially driven by reinforcement learning, in which politicians expressed more incivility in response to more positive feedback (e.g., 'likes' and 'retweets') [29]. The same study found that this increase in incivility was not found in offline political debates or congressional speeches, suggesting a mismatch between the online and offline world. However, there has also been a general increase in offline feelings of political sectarianism in representative surveys of US citizens [105].

Another recent study found persistent patterns of toxicity across 34 years of social media data, suggesting that, while social media has evolved tremendously, online conversation patterns have remained remarkably consistent [118]. Other work found that belief in conspiracy theories has not increased over time and that the advent of social media has not coincided with an increase in conspiracy belief [119]. Altogether, these longitudinal results leave us with conflicting findings: while they show us that certain aspects of information spread are remarkably consistent (likely due to similar underlying psychological processes), they also demonstrate how structural features of the modern information environment may have altered information spread.

certain contexts (such as a crowded room), structural features of online or offline environments can also shape information spread. We briefly review some structural factors that may shape information spread below.

Face-to-face interaction (or lack thereof)

A common assumption is that people's behavior becomes more hostile behind the anonymity of the internet. However, one study suggests that this assumption is overstated: people who are hostile online are also hostile offline, as opposed to online anonymity suddenly making nonhostile individuals hostile [87]. Social media may instead feel more hostile because hostility is more visible, potentially because of algorithms [6], the size of online networks enabling 'superspreader' dynamics [81], and other factors. This study supports the idea that the offline and online world are similar in underappreciated ways.

Nevertheless, the lack of face-to-face contact in online spaces may still have important consequences. For instance, one study found that conversations about controversial political issues were less productive when they happened over text (rather than face-to-face or via video call) [88], suggesting that certain features of online discourse are more hostile.

Algorithms

Unlike offline environments, online environments are mediated by algorithms. This can have both positive and negative consequences: while some work suggests that algorithms can filter out uncivil language and low-quality news [89], the fact that algorithms amplify attention-grabbing content means that they can also amplify high-arousal negativity and other forms of content that people do not want to see but is nonetheless engaging [24]. Indeed, a recent audit of the Twitter/X algorithm found that it amplified political content that did not align with people's stated preferences, such as emotionally charged content and out-group negativity [55].

Design features

Other design features besides algorithms alone may further impact information spread. As one example, some have hypothesized that the ease with which information can be reshared without friction facilitates the spread of polarizing and false content [90]. Indeed, a large field experiment conducted in collaboration with Meta found that eliminating the 'reshare' feature reduced the amount of false news and political content that spread [91]. Thus, decreasing the ability for content to go 'viral' quickly may be a solution to reduce the spread of misinformation or extreme content. Indeed, WhatsApp has implemented limits on how much a message can be forwarded to try to slow the spread of misinformation [92]. Furthermore, providing some other way for people to signal their disapproval of posts, such as via a 'dislike' or 'distrust' button [70,93], could reduce the virality of widely disliked content.

Norms

For decades, social psychologists have noted the power of social norms in shaping behavior [94]. Norms also powerfully shape online behavior. For instance, one study found that norm learning influences the sharing of moral outrage online [8]. One also might expect that the norms of various social media platforms might differ. Indeed, recent research suggests that, on more liberal platforms (e.g., BlueSky), more liberal leaning news sources go viral, and vice versa for conservative platforms (e.g., Truth Social) [95]. The norms within a platform can also rapidly change. For instance, after Elon Musk's purchase of Twitter/X and implementation of numerous design changes, people began posting more low-quality news on the platform, potentially because of a change in norms (as well as design features, algorithms, and other structural features) [80].

Network size and structure

Another reason why online information spread is different from offline information spread is that the online world has much larger social networks. The sheer size of online networks allows for 'superspreader' dynamics that could not exist in the offline world. For instance, while an individual can spread a harmful rumor to dozens of their offline connections, the spread of this rumor offline would not compare to the spread facilitated by an account with millions of followers. One study found that, while some people spread more gossip compared with others (implying the existence of gossip superspreaders), those who gossiped most frequently had fewer friends, suggesting that gossip superspreaders have limited reach offline [96]. This contrasts with the online world, where superspreaders with the most extreme voices typically have the broadest reach [97].

Beyond size, other network properties may impact virality. For instance, studies have found that weak social ties are more responsible for the spread of anger [33] and novel information [98]. The online world has many more weak ties compared with the offline world, which may substantially influence the amount of angry and novel information that people are exposed to online. Social media **echo chambers** may also impact the diffusion of information [99]. For example, moral and emotional language predicts the sharing of information within (but not between) political echo chambers [7]. However, echo chambers also exist offline, and there is debate over the extent to which online versus offline echo chambers differ [100].

A global perspective on virality

One limitation of the literature on the psychology of virality is that most work is based on English-language data from Western contexts. While there may be some universal factors that attract attention and lead people to spread information, there are important cross-cultural differences. With the advent of large language models (LLMs), it has become easier to analyze data from multiple different languages and cultures around the world and explore cross-cultural differences in the spread of information [101,102].

Some previous studies observed cross-cultural differences in information spread. For instance, while high-arousal negativity tends to be more 'contagious' in a Western, individualist context (i.e., the USA), high-arousal positivity tends to be more contagious in an Eastern, collectivist context (i.e., Japan) [103]. In addition, while out-group animosity (or, more broadly, identity-related content) has repeatedly been shown to go viral in the USA [6,25–27,104], this may be partially due to the fact that the USA is a unique political context, marked by particularly high levels of political sectarianism [105]. Indeed, in-party love spreads more efficiently on Twitter/X in Spain compared with out-party hate [47]. Another study, looking at the Russia–Ukraine war, found that out-group animosity appeared to be a stronger predictor of virality in Ukraine before the Russian invasion, but in-group solidarity surged as the strongest predictor of virality after the Russian invasion [48]. This suggests that external threats are a structural feature shaping information spread. While most studies on virality have focused on one culture at once, Box 3 suggests that future work should analyze and compare many countries and cultures simultaneously to examine the key variables driving cross-cultural differences.

Concluding remarks

We have integrated diverse literatures, including psychology, neuroscience, communications, political science, computer science, network science, marketing, and more, on the psychology of virality. While this topic has recently been explored extensively in the context of social media, our review finds that similar types of information tend to spread across multiple contexts: online, offline, and historically. We have outlined how cognitive and social processes (e.g., attention, motivation, etc.) interact with structural features (e.g., algorithms, incentives, network structures, etc.) to shape information spread. To better understand the interplay of these factors in shaping virality, future work should explore what goes viral across language, cultures, and contexts (see Outstanding questions). Understanding the psychology of virality is crucial because what goes viral dictates what people consume in their information diets, and evolving technologies (e.g., social media, AI, etc.) are rapidly changing how information spreads.

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Box 3. The future of virality

Much previous work on the psychology of virality has relied on **dictionary methods** (e.g., counting the number of negative or positive words in a social media post). However, LLMs have transformed psychological text analysis and can allow for a more granular understanding of what goes viral. LLMs, such as GPT, have been found to be much more accurate at detecting human-annotated psychological sentiment compared with dictionary methods [101] (Figure I). They also accurately classify text across languages, including several lesser-spoken and under-resourced languages [101]. Another way in which LLMs can improve the study of virality is by allowing for more sophisticated agent-based models, which can model how information spreads through online and offline networks [120].

These methodological advances allow us to study the type of information that spreads across many more languages and cultures, which could make broader, cross-cultural analyses of virality easier, given the multilingual effectiveness of modern LLMs [101]. However, these cross-cultural studies are still dependent upon data from social media platforms, which are becoming increasingly less available [121]. A few cross-cultural studies have looked at several countries at once, finding some cross-cultural similarities in online interaction patterns [50,122]. For instance, one paper found that right-leaning political parties were amplified by Twitter/X's algorithm across several political systems [122]. However, even larger studies can look more systematically at how information spread is moderated by important variables (e.g., country-level individualism-collectivism, income-level, inequality, etc.), which would help construct a more global theoretical account of the psychological and structural features that shape information spread. Given that the online and offline world is becoming increasingly intertwined, future work should also explore how online information spread impacts offline information spread and behavior (and vice versa). As an example of this, some scholars have linked online rhetoric to voting behavior[vi] and protest behavior [123].

Outstanding questions

What psychological processes drive information sharing and consumption?

Do similar factors predict information spread in offline (as opposed to online) contexts?

Does the information-as-virus metaphor accurately describe the spread of information? Does this metaphor change how people think about the spread of (mis)information?

Did similar factors predict information spread historically? Would analyzing data from early newspapers and other early text find that similar factors predicted virality long before the advent of social media?

How do structural features of modern technologies (e.g., algorithms, platform design, network size, etc.) influence the spread of information? How do these structural features interact with psychological processes to shape information spread?

Are there cross-cultural differences in information spread? What cultural variables influence the spread of information?

Can advances in AI (e.g., text analysis or agent-based modeling via LLMs) help us better understand how information spreads?

How does online behavior impact offline behavior, and vice versa? How do online and offline networks interact?

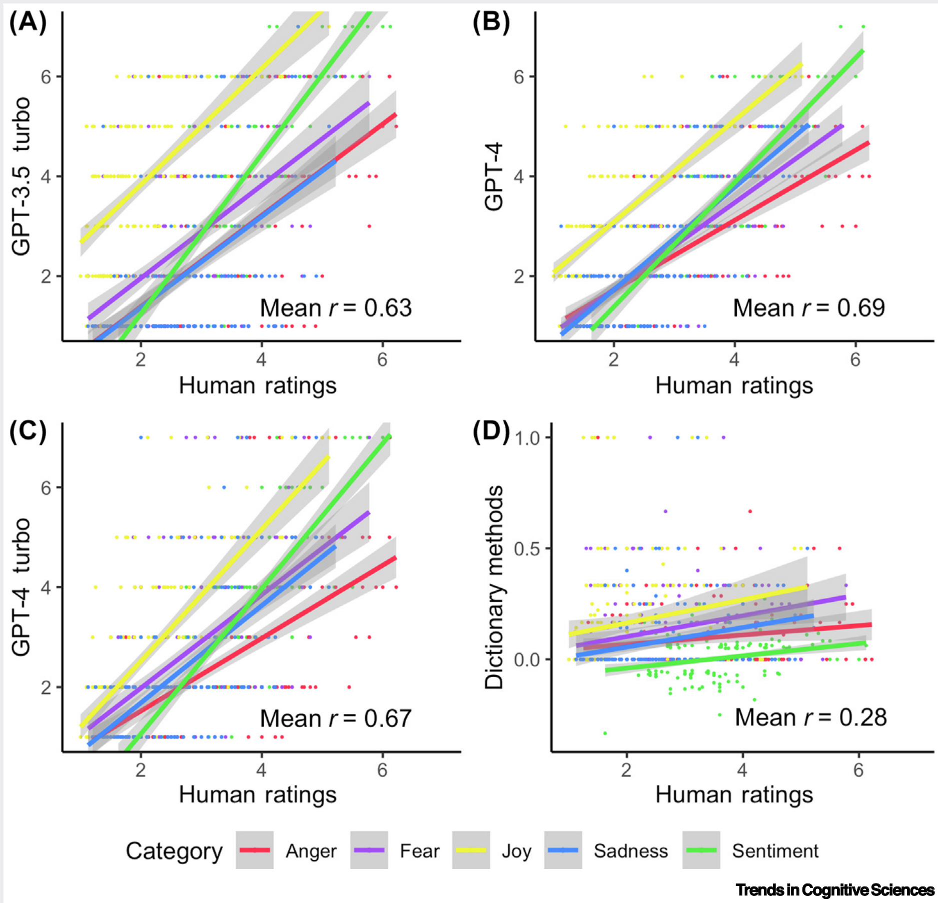

Figure I. Large language models (LLMs) can help advance the psychology of virality. Various versions of the popular LLM GPT [including (A) GPT-3.5 Turbo, (B) GPT-4, and (C) GPT-4 Turbo] were much more accurate at detecting manually annotated sentiment and discrete emotions (with mean correlations of 0.63–0.67) compared with (D) dictionary-based text analysis (with a mean correlation of 0.28). GPT also worked well across languages, which can help facilitate more cross-cultural and multilingual research. Furthermore, open-source LLMs are rapidly improving, which can help facilitate inexpensive, open, and reproducible research. Adapted from [101].

Declaration of interests

None declared by authors.

Resources

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[ii] https://books.google.com/books?id=_OcCAAAAMBAJ&printsec=frontcover#v=onepage&q&f=false

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