Combining interventions to reduce the spread of viral misinformation

Joseph B. Bak-Coleman[a,b,c,*], **Ian Kennedy**[a,d], **Morgan Wack**[a,e], **Andrew Beers**[a,f], **Joseph S Schafer**[a,f], **Emma S. Spiro**[a,c,d], **Kate Starbird**[a,g], **and Jevin D. West**[a,c]

[a]Center for an Informed Public, University of Washington, Seattle, WA 98195
[b]eScience Institute, University of Washington, Seattle, WA 98195
[c]The Information School, University of Washington, Seattle, WA 98195
[d]Department of Sociology, University of Washington, Seattle, WA 98195
[e]Department of Political Science, University of Washington, Seattle, WA 98195
[f]Paul G. Allen School of Computer Science and Engineering, University of Wasington, Seattle, WA 98195
[g]Human Centered Design and Engineering, University of Washington, Seattle, WA 98195
[*]Corresponding Author: joebak@uw.edu

ABSTRACT

Misinformation online poses a range of threats, from subverting democratic processes to undermining public health measures[1–3]. Proposed solutions range from encouraging more selective sharing by individuals, to the removal of false content and accounts that create or promote it[4,5]. Which strategies to implement depends on their relative and combined ability to reduce viral misinformation spread at practical levels of enforcement. Here we provide a framework to evaluate interventions aimed at reducing viral misinformation online both in isolation and when used in combination. We begin by deriving a generative model of viral misinformation spread, inspired by research on infectious disease. Applying this model to a large corpus of misinformation events that occurred during the 2020 US election, we reveal that commonly proposed interventions–including removal of content, virality circuit breakers, nudges, and account banning—are unlikely to be effective in isolation without extreme censorship. However, our framework demonstrates that a combined approach can achieve a substantial ($\approx 50\%$) reduction in the prevalence of misinformation. Our results challenge claims that combating misinformation will require new ideas or high costs to user expression. Instead, we highlight a practical path forward as misinformation online continues to threaten vaccination efforts, equity, and democratic processes around the globe.

Introduction

Misinformation–i.e. false information– has become a pervasive feature of online discourse, resulting in increased belief in conspiracy theories, rejection of recommended public health interventions, and even genocide[1,3,6,7]. Academics and those working in industry have proposed a host of potential solutions, ranging from techniques for detecting and removing misinformation to empowering users to be more discerning in their sharing habits[4,5,8]. Despite an abundance of proposed interventions, online misinformation remains a global problem[1,2,9]. For instance, the 2020 US Presidential election and subsequent insurrection at the capital building highlighted how pervasive online misinformation online can lead to real-world harm.

That real-world violence occurred as a result of a broader narrative that questioned the election's legitimacy, which arose from a series of more specific claims. Most claims were characterized by a brief period (i.e. hours, days) of rapid growth in discussion and sharing[3]. During these events, engagement (i.e. all discussion and sharing) exhibits viral, disease-like dynamics—self-replicating, endogenous growth stemming from a limited number of initial sources[10,11]. Some of these incidents quickly died out, while others had multiple waves, spread to other platforms, and often became consolidated into broader narratives.

Early response provides a source of promise for successful intervention, as disrupting viral spread may have cascading effects on narrative consolidation and future engagement. Unfortunately, the rapid growth inherent to viral misinformation makes it challenging to assess and respond to in a timely manner. Productive intervention by platforms and policy makers requires a temporally-aware framework for quantitative comparison of proposed interventions.

Lacking this, it is unclear whether existing strategies are sufficient to produce meaningful results. Crude approaches like outright removal and banning of either content or accounts will certainly work if applied in excess, yet come with costs to freedom of expression and force private entities to be arbiters of truth. For judicious use, questions arise about how soon and how much removal is necessary for a meaningful effect. Similarly, interventions that rely on empowering individuals to consume and share more discerningly have shown promise in experimental contexts, but it remains unclear what impact they will have at scale[4].

Beyond comparison, we lack an understanding of when—and indeed whether—multiple interventions can act synergistically to reduce the spread of misinformation. Toward this goal, we derive and parameterize a generative model of misinformation engagement (i.e. total discussion and sharing of posts related to false information) using a large corpus of tweets collected during the 2020 election in the US[3]. We rely on this model to examine the efficacy of misinformation interventions both in isolation and when deployed in combination. Finally, we examine how the spread of misinformation during viral periods impacts subsequent engagement.

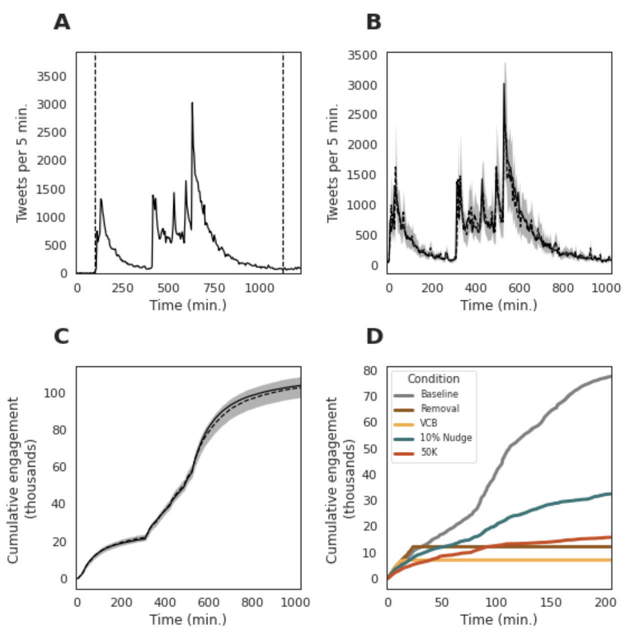

Figure 1. Overview of our model and analysis **A)** An event segmented from a larger incident (dashed lines). **B)** Time-series for a single event, here a later-recanted story about a poll worker in Pennsylvania admitting to ballot tampering. Dashed-line: expected value, shaded region: 89% credible interval (CI). **C)** Cumulative engagement as a measure of total misinformation, lines and shading are as in B. **D)** Model-simulated platform interventions for a single event. Lines indicate median cumulative engagement over 100 simulations. Grey: baseline, purple: 10% "nudge", orange: banning, yellow: virality circuit breaker, green: outright removal of content

Results

Overview and Model

We begin by deriving a generative model of misinformation spread that relies on a few simple assumptions. First, that a users' audience can be approximated by their follower count[12,13]. Next, that within an event the spread of misinformation resembles a simple contagion whereby only a single interaction is necessary for transmission[14,15]. We further assume that dynamics during a viral event are predominantly endogenously-driven within a single platform rather than via other processes (e.g cable news, cross-platform). Finally, we assume that discussions on a topic decay over time as new topics replace them and reach saturates. These phenomena can be captured by a minimally parameterized branching process model, such that:

$$
\begin{aligned}
\mathbb{E}[y_t] &= \exp(\alpha + \beta v_{t-1}) \\
v_t &= v_{t-1}\delta e^{-\lambda t} + x_t \\
x_t &= \log(\sum_{j=1}^{y_t} F_{j,t})
\end{aligned}
\tag{1}
$$

Where y_t are the posts (i.e. retweets, tweets, replies, quote tweets) at time t, α is the baseline rate of discussion, and β is the effect of virality, v. Virality is a proxy for the total number of users at a given point in time that are exposed to and may propagate misinformation. Virality decays as an exponential function via δ and λ. Here, δ captures the baseline rate of decay per time step, and λ controls the way in which that decay changes over the lifetime of an event. This could either be due to algorithmic processes favoring new content or, for very large events, user saturation. Every time step, for each of y_t accounts that posts, the log sum (x_t) of their followers, F_j is added to virality for the subsequent time step. Our model bears similarity to those used to evaluate interventions and super-spreading in infectious disease[16].

Rather than solving this model analytically, we instead rely on a computational approach with parameters estimated from 216 events ($\approx$ 6M posts) of rapid misinformation spread observed online during the 2020 US election (See Methods). This allows us to draw from an empirical distribution of follower counts specific to a given event and study the effect on engagement of banning users in a manner that is conditioned on their real-world patterns of behavior. We estimated the parameters of the model for each event using Bayesian inference, generating posterior predictive time-series to evaluate fit for each event (Fig 1B-C, Methods). Using the data-derived parameters, we simulated the impact of platform interventions on cumulative engagement across all events (See Methods, Fig. 1D). Posterior predictive plots for all 216 events are presented in the SI.

Fact-Checking and time-lagged approaches

We begin by considering the impact on user engagement of approaches in which a platform applies policies that target a specific instance of misleading or false information–in this case individual posts. Among the more commonly employed strategies during the 2020 US election was identifying specific misinformation and taking action, ranging from applying a label to outright removal[3]. These approaches share a common feature of requiring time before action is taken. Time is necessary to not only identify the misinformation, but also to decide on an appropriate response.

In an extreme case, a platform could remove or hide all content matching search terms related to an emerging misinformation incident. To simulate this, we ran our model until time t, at which point growth stopped entirely (Fig 2A). Our results indicate that outright removal can indeed be effective, producing a dramatic 93.5% median reduction in total posts (i.e. tweets, replies, quote-tweets, and retweets) on the topic if implemented within 30 minutes (89% C.I. [92.4, 94.2]). Even with a 4 hour delay, our model indicates reductions of 50.5% (89% C.I. [47.6, 52.9], Table S1). These effects generously assume that platforms are able to monitor, detect, sufficiently fact-check (for ethical considerations) and implement a full removal response within the specified time-frame. As such, the efficacy is dramatically reduced if only a fraction of events lead to action (Fig 2B, Table S2).

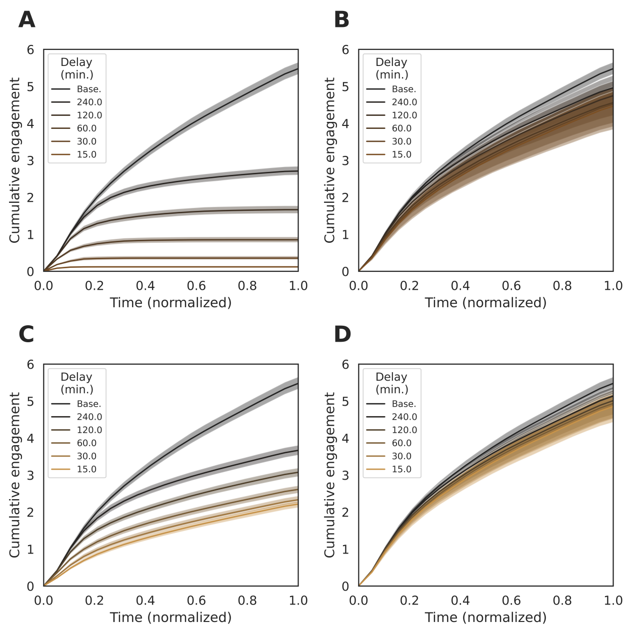

Figure 2. **A)** The impact of outright removal on of all misinformation-related posts following a delay specified in minutes. Time (x-axis) is normalized to the duration of the event. **B)** As in A if only 20% of events are removed. **C)** The impact of applying a virality circuit breaker that reduces virality by 10% to all misinformation events after a specified period of time. **D)** As in C, if the VCB is applied to only 20% of events.

A more plausible approach could involve "virality circuit breakers" which seek to reduce the spread of a trending misinformation topic without explicitly removing content, for example by suspending algorithmic amplification[17]. This approach allows platforms to consider ethical ramifications while minimizing the public relations challenges that can accompany direct forms of action. This could aid in lowering the threshold for fact-checking, enabling quicker response times. We simulate the impact of virality circuit breakers by reducing virality after a period of time such that $\hat{v}_t = v_t * (1-p)$, where p is the proportional reduction in virality (See Methods).

Through simulations, we reveal how virality circuit breakers can have similar efficacy to outright removal even if the amount by which virality is reduced is small (Fig. 2B, Table S3). For instance, a 10% reduction in virality, implemented four hours after the start of an event, can reduce the spread of misinformation by nearly 33.0% (89% C.I. [29.7 36.3]). As with outright removal, however, the efficacy is primarily limited by the proportion of events for which the platforms take action (Fig 2D, Table S2)

Nudges and reduced reach

A drawback of fact-checking based approaches is that they are most applicable to transparently false or readily falsifiable claims[3]. Many instances of misinformation involve claims that are either partly true, or require non-trivial time to debunk. Depending on implementation, time-lagged responses may further require that users are receptive to the intervention, or do not find ways around removal or platform action.

These challenges motivate approaches that leverage individual discretion to reduce to spread of misinformation[5]. For instance, encouraging users to consider accuracy has been shown to reduce rate at which individuals share misinformation by 10-20%[4]. AI-based approaches could likewise scan drafts of posts and warn users if they appear to be amplifying misinformation.

A central question is whether a modest reduction in individual sharing behavior can lead to a more dramatic change in overall rates of misinformation. Agent-based models support this notion across a range of network topologies[4]. From the perspective of our model, nudge-based approaches can be simulated by maintaining the parameters from the initial model fit while proportionally reducing the following of every user that discusses an incident. Recall Eqn. 1: from the perspective of the model a nudge, η, can be implemented such that $\hat{F}_{j,t} = (1-\eta)F_{j,t}$ where $0 < \eta < 1$.

Using our model to simulate nudges, we find that they can indeed reduce the prevalence of misinformation (Fig 3A, Table S5). Nudges that reduce sharing by 5, 10, 20, and 40% result in a 6.6, 12.4, 22.6, and 38.9% reduction in cumulative engagement, respectively (Table S5). The median effect tends to be larger than the nudge suggesting a degree of feedback whereby the individual effect of a nudge is compounded in the misinformation dynamics.

Account Banning

In our dataset, several accounts shared or amplified misinformation across multiple incidents[3]. Moreover, some of these repeat offenders had out-sized audiences when compared to the average Twitter user—ranging hundreds of thousands to millions of followers. While removal of repeat offenders during the election was rare, several were removed following the violent insurrection at the US capital on January 6, 2021. A question remains whether the removal of these accounts, or account-focused policies in general, would have a meaningful impact on misinformation. While large-followings often confer engagement, it remains possible that there is sufficient sharing from smaller accounts to ensure the spread of misinformation even in the absence of the larger removed accounts[18].

One challenge in modeling account removal is that there likely exists non-trivial relationships between account-size, propensity to share misinformation, and the timing at which certain accounts amplify narratives. A large account that regularly shares misinformation in the first five minutes will have an out-sized effect compared to a smaller account that occasionally shares misinformation hours later. To account for this, our model samples from the empirical follower-count distribution in a given time step. Further, as identities of individuals are known, we can remove specific accounts and simulate total engagement (See Methods). In other words, our simulations are conditioned on unseen patterns of, and variation in, individual behavior without explicitly quantifying the differences in individual behavior. Through this, our model and simulations exhibit robustness to considerable unmeasured real-world complexity.

We begin by considering the consequences of account removals ($N = 1504$) that occurred in early 2021. We seek to answer whether previously implemented account removal is sufficient to curb misinformation going forward. Our simulations reveal that the removal of these accounts from our dataset reduces total engagement with misinformation by 12.0%, (89% C.I. [8.4, 15.8], Fig 3C). This is comparable in efficacy to a 10% reduction in sharing of misinformation (i.e. a nudge) impacting all accounts in the absence of removal.

We next consider a "3 Strikes" rule in which accounts are removed from the platform after they are detected in three distinct incidents of misinformation (i.e. topics, regardless of number of posts for a given topic). For these simulations, any interaction or amplification of misinformation (i.e. tweets, retweets, quote tweets) would be counted as a strike. A policy focused solely on original content could be gamed by using large accounts to amplify disposable smaller accounts. This type of policy would avoid banning accounts that were swept up by a given piece of misinformation and tweeted repeatedly, while focusing on those that spread misinformation more broadly. Applied solely to verified accounts, we observe a 7.8% drop in cumulative engagement (89% C.I. [4.1, 11.7]) which likewise is similar in efficacy to a small nudge rolled out across the board (Table S6, Fig. 3C). If, instead of verification, the policy is applied based on the number of followers an account has, pronounced effects are only observed when the threshold is quite low ($\approx 10{,}000$ followers) requiring large numbers of accounts to be removed (Fig. 3B and D, Table S7).

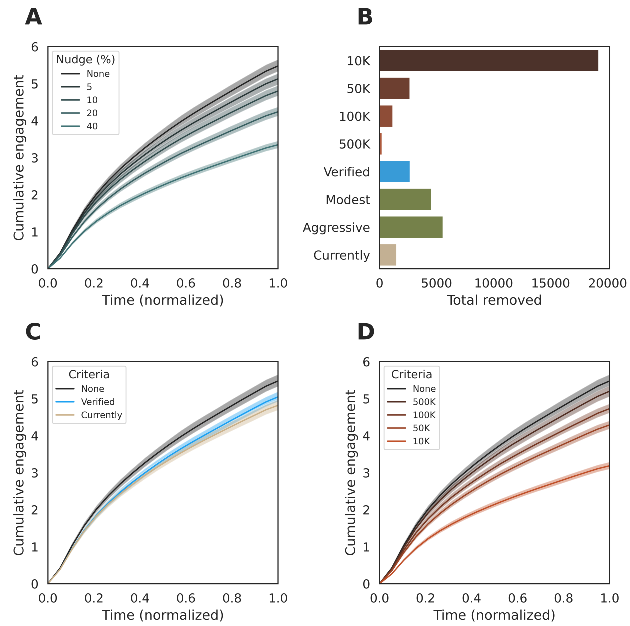

Figure 3. **A)** The effect of nudges that inoculate a percentage of the population against spreading misinformation. Shown is the cumulative total engagement across all events, with time normalized to the duration of the event. **B)** Number of accounts that are either currently removed, or would have been removed under a three-strikes policy **C)** The effect of accounts removal for either those that are currently banned (orange) or those banned following a three strikes rule applied solely to verified accounts (blue). **D)** As in A and C, yet showing the impact of enacting three-strikes policies with varying thresholds.

Combined Approaches

All of the approaches above exhibit some efficacy reducing engagement with viral misinformation. Unfortunately, each strategy tends to become maximally effective in impractical regions of parameter space. Outright removal of misinformation is particularly effective, yet it is difficult to imagine that more than a small fraction of misinformation can be easily removed. Virality circuit breakers face similar challenges, albeit to a lesser extent. For nudges that minimally impact user experience yet improve individual discretion, effects far beyond $\approx 20\%$ are unlikely without a major breakthrough in information literacy or social psychology[4]. In the case of banning specific accounts, low follower thresholds increase the number of accounts removed, and thus costs and challenges, super-linearly.

We therefore consider a combined approach relying on only modest implementations of each of the strategies studied above. Specifically, viral circuit breakers are employed for 5% of content, reducing virality (v_t) by 10%, and enacted after 120 minutes (i.e. for ≈ 11 events). Among the content that is subjected to a viral circuit breaker, 20% is subsequently removed outright after four hours (≈ 2 events). We further assume a 10% reduction in individual sharing of misinformation resulting from a nudge. Finally, accounts that have been removed remain banned, and a 3-strikes policy is applied to verified accounts and those with more than 100K followers. Our model reveals that even a modest combined approach can result in a 36.3% (89% C.I. [31.4, 41.8]) reduction in the total volume of misinformation (Figure 4A, Table S8).

We additionally consider a more aggressive version of a combined policy, applying viral circuit breakers to 10% of content and reducing virality by 20% while cutting response times in half. We further assume a 20% nudge, and reducing the threshold for the 3-strikes policy to 50K followers. This more aggressive approach dramatically reduced misinformation by 48.8% (89% C.I. [43.4, 54.9], Figure 4D, Table S9). Similar efficacy from standalone approaches would either be impossible ($>$ 40% Nudge) or require draconian removal of content and accounts.

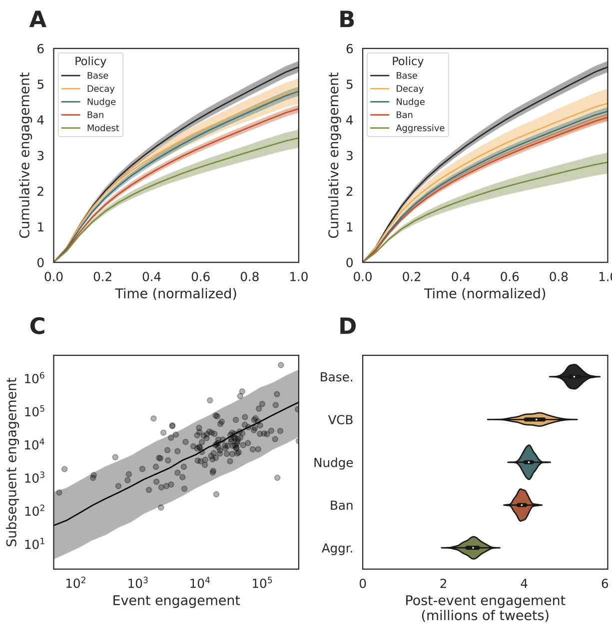

Figure 4. A) The impact of a modest combined approach to intervention (described in text, green) and each intervention applied individually (as per legend) **B)** The impact of a more aggressive combined approach (described in text, green) and each intervention applied individually (as per legend) **C)** Relationship between engagement within the largest viral event for a given incident and subsequent engagement **D)** Expected post-event engagement given action taken during an event.

One limitation of our model is that it relies on assumptions specific to periods of viral misinformation spread. In our dataset, only 40% of posts occur during the largest event for a given incident. Yet 48% of engagement occurs after the largest event. While our model cannot provide direct insight into how interventions will impact engagement during these periods, we can gain indirect insight by considering the relationship between the size of an event and subsequent discussion.

Our data demonstrate that the size of an event is strongly predictive of subsequent engagement (Fig. 4C, Bayesian Log-Normal Regression $\beta = .95$, 89%C.I. [.93, .97], Table S10). Using this relationship, we can estimate subsequent discussion based on simulated, intervention-adjusted engagement during the largest event (See Methods). Through this, we reveal that the impact of interventions on post-event engagement is likely to be similar in magnitude to the efficacy during an event (Fig. 4D, S7).

Conclusions

Our derived model, grounded in data, provides quantitative insight into the relative efficacy of proposed interventions. Through simulation, we reveal that proposed interventions are unlikely to be effective if implemented individually at plausible levels. Effective removal of content or virality circuit breakers would require large teams, rapid turn-around times, and place content decisions squarely in the hands of private organizations. Nudges are promising but unlikely to be a panacea at known levels of efficacy[4]. Banning appears the most workable solution, but would require removal of tens of thousands of users to be effective.

Fortunately, our results show that combining interventions at plausible levels of enforcement can be effective at reducing misinformation. While it is unsurprising that multiple interventions outperform individual approaches, our paper provides necessary insight into the magnitude of that difference. The efficacy of a combined approach is dependent not only on the nature of individual interventions, but how they interact with one another, the dynamics of misinformation spread, event duration, user sharing behavior, user follower counts, and how these factors change throughout the course of a disinformation campaign. In fitting our model to a large corpus of events during an active period of mis- and disinformation, our results are conditioned on much of this complexity. Further, by drawing from the empirical distribution of users' follower counts, our model indirectly and implicitly accounts for unseen behavioral patterns of users and changes to their follower counts over time.

What remains unclear is how changes in the magnitude of events will impact longer-term dynamics of misinformation and translate to a reduction in harm. If implemented in tandem, it may prove a sufficient shock to collapse the misinformation ecosystem altogether, as shock-induced collapse is a central feature of complex systems[19]. For instance, subsequent events likely depend on the size of previous events, and breaking that feedback could lead to greater than expected gains. However, this same body of literature suggests that an insufficient shock may yield only short-term changes as the system re-organizes and adapts. For this reason, rolling out policies individually and insufficiently may make the problem harder to solve in the long term.

We note that the results presented here rely on a simplified model of events on a single platform in what is a highly complex, multi-platform system. These types of simplifications are an inherent limitation of any approach, short of risky, large-scale experimentation. However, abstract models of complex processes have proved essential to predicting the benefits of interventions on complex systems, from the mitigating the spread of disease to stabilizing ecosystems[16,20]. Models provide particular utility when experiments are unethical and impractical, and costs of inaction are high. Given the substantial risks posed by misinformation in the near term, we urgently need a path forward that goes beyond trial and error or inaction. Our framework highlights one such path that can be adopted in the near-term without requiring large-scale censorship or major advances in cognitive psychology and machine learning.

1 Methods

1.1 Data Collection and Processing

Our dataset was collected in real-time during the 2020 US election. We relied on an evolving set of keywords to collect data from Twitter's API. Keywords were updated in response to new narratives, for instance adding "sharpiegate" and related terms after false narratives emerged about the use of Sharpie markers invalidating ballots. Working with the Electoral Integrity Partnership, we catalogued instances of misinformation that were either detected by the team or reported by external partners[3]. This led to a large corpus of tickets associated with validated reports of misleading, viral information about election integrity.

Tickets that shared a common theme were consolidated into incidents. For each incident, we developed search terms and a relevant date range in order to query posts from our tweet database. Incidents ($N_i = 153$) were generally characterized by one or more periods of intense activity followed by returning to a baseline state (Fig 1A). Search terms and descriptions of incidents are provided along with the data. The time-series of all related posts from each incident was grouped into five minute intervals and segmented into distinct periods of increased activity, events ($N_E = 216$, See Methods, Fig 1).

Event segmentation and inclusion criteria

Each of the 154 incidents misinformation was characterized by one or more periods of viral spread (i.e. events). Long periods of low activity between events would violate the assumptions of our statistical model, requiring segmentation of incidents into discrete events. We began segmenting by grouping collected posts into 5 minute intervals, and finding the interval within the aggregated time-series that had the highest volume of collected posts. Other peaks in activity were considered part of separate events if they were at least 30% of the magnitude of the largest peak (to filter out noise). Event boundaries were determined as the points before and after the peak where the number of posts in 5 minutes was less than 5% of the maximum volume. If this did not occur within the range of data collection, the first (or last) time-point collected was used to denote the beginning (or end) of an event. Finally, events were required to last at least an hour (i.e. 12 data points)

Using this initial corpus of 260 events, our model was fit to each event using PyStan[21,22]. We fit events separately (rather than hierarchically) as they varied widely in their time scales, magnitudes, and context within the broader 2020 election cycle. These factors, combined with computational limitations, precluded a full hierarchical model from being feasible or appropriate. Similarly, our model was unlikely to be appropriate for all events as it makes assumptions post volume is well predicted by the number of previously exposed accounts on twitter. If, for instance, an incident received substantial news coverage (i.e. Dominion software narratives) our model would likely fail.

To safeguard against this, we relied on a number of criteria to ensure model fit to a given event. Events were included in the final analysis if a) the posterior 89% C.I. of total posts contained the observed value and b) the chains successfully converged for all parameters ($\hat{R} < 1.1$) c) The fit did not contain divergent transitions and d) the event lasted longer than an hour (i.e. > 12 data points to fit). Other than these criteria, events surrounding the dominion narrative were removed as they involved long periods high volume online discussion. This filtering processes resulted in inclusion of 216 events (81% of total events), and $\approx 6M$ posts. We note that, in the main text, we consistently see a slightly smaller ($\approx 5\%$) number of cumulative posts in our baseline condition. We suspect this is due to non-randomness in the relationship between follower counts and the probability of being involved in a tweet (we sample randomly) and/or the absorbing boundary of zero posts in our model.

Statistical and Computational Model

1.2 Model Justification

The spread of misinformation online occurs on complex networks involving aspects of both organic growth and coordinated disinformation campaigns. Acceptance of a given misinformation narrative likewise involve a complicated cognitive process involving partisan leanings, prior knowledge, attention, the message content, and a host of other factors[4,23]. At face value, it would appear unlikely that a minimally parameterized model could adequately capture the generative process and provide useful insight. Yet, a similar argument could be invoked regarding the spread of disease which involves non-trivial behavioral, fluid, and immune dynamics. Nevertheless, compartment models (e.g. SIR, SEIR) have become essential epidemiological tools in the century since their introduction[16,24,25]

Models of complex process provide useful insight when they capture the leading-order terms drive a system's dynamics[26]. Here we assume that the dynamics are driven primarily by the number of people previously exposed and declining engagement through saturation or replacement with new content. The ability of our model to recreate patterns of engagement provides indirect evidence that it captures key phenomena (See S1). Finally, we note that previous work has leveraged epidemiological models to understand the spread of viral memes[11].

Our model does not explicitly capture some key features of misinformation spreading online. Most notably, there is no notion of a network despite the fact that misinformation clearly spreads through one on Twitter. If, for instance, a retweet occurs in a relatively unexposed portion of a network it may result in more subsequent posts than if it arises in a saturated region. Here, our choice of link function, a mixture of gamma and Poisson distributions (i.e. negative binomial) is critical. This type of distribution arises when there is some underlying rate, as in a Poisson, that varies according to a gamma distribution. In the context of our model, the contribution of a users' followers to the rate (as a Poisson distribution) of posts in the next time step is free to vary (as a gamma distribution) when it wanders into different portions of the network. There is substantial precedence for modeling simple contagion on networks using similar distributional assumptions[16].

Further, we note that our model relies on the strong assumption that spreading is endogenous to Twitter and that the impact of cross-platform dynamics can be ignored for the purpose of our analysis. During the election, there was ample evidence of information being posted cross-platform, often by the same users[3]. This could prove problematic if, for instance, the majority of posts on a topic were original tweets copied and pasted from another platform. Within an event, however, original tweets tend to comprise only a small fraction of total posts, suggesting that growth during an event is largely a result of endogenous growth on Twitter (i.e. responses to things seen on Twitter). Most importantly, we would not expect our model to fit our data if cross-platform forces were leading-order terms in the dynamics. Nevertheless, we note that cross-platform dynamics are likely to play a more pronounced role on longer time-scales and methods for measuring and mitigating their impact on misinformation dynamics are urgently needed.

Statistical Model

We model the growth of misinformation as a branching process in which posts (and thus virality) in subsequent time steps is a function of activity in previous time steps. Posts y_i at time t are assumed to be distributed as a gamma-poisson mixture (i.e. negative-binomial) with expected value μ_t Specifically:

$$
\begin{aligned}
y_t &\sim \text{NegativeBinomial2}(\mu_t, \phi) \text{ for } t = 2...T \\
\mu_i &= \exp(\alpha + \beta v_{t-1}) \text{ for } t = 2...T \\
v_t &= v_{t-1}\delta e^{-\lambda t} + x_t \\
\alpha &\sim \text{Normal}(-3, 3) \\
\beta &\sim \text{Normal}(0, 3) \\
\delta &\sim \text{Beta}(2, 2) \\
\lambda &\sim \text{HalfExponential}(1) \\
\phi &\sim \text{HalfExponential}(1) \\
v_1 &= x_1 \\
x_t &= \log\Big(\sum_{j=1}^{y_t} F_j + 1\Big)
\end{aligned}
$$

Where α is the baseline rate of detection for related keywords and β is the effect of virality, v. Virality is calculated as a decaying function of v_{t-1} and the log of the sum of account follower counts F_j for posts in the previous time step. One follower is added to each user to avoid an undefined value in time steps with no followers. The log transform accounts for the link function (exp) transforming the linear model into an expected value for the Negative Binomial distribution. Given the wide range of possible event shapes, generic, weakly informative priors were chosen for all parameters. Models were fit using HMC in Pystan with default sampling parameters[21,22].

Computational Model

Our computational model relied on the posterior distributions of parameters obtained from fitting our statistical model separately to each event. For each simulation, one sample was drawn at random from the posterior for a given event. At $t = 1$, the model was initialized with the volume of posts and total engagement from the first time step in which any posts were observed. At each subsequent time step, our computational model predicted the number of new posts, y_t, by sampling from a negative binomial distribution as per our statistical model. For each of y_t new posts, we drew a follower count from the actual distribution of accounts that retweeted for that event, at that time step. Doing so allowed us to control for the possibility that some accounts tend to appear earlier in a viral event. This processes was repeated for the duration of the actual event.

We simulated removal of misinformation by simply setting $y_{t+1} = 0$ after at a specified intervention time, t. Virality circuit breakers were enacted by multiplying virality at each time step by a constant. For example, a 10% reduction in virality was implemented as $\hat{v}_t = v_t(1 - .1)$. As with the removal, this occurred only after a specified time step. In the case of the combined approach, virality circuit breakers (and subsequent removal) were employed at a given probability for each run of the simulation. Nudges were implemented through multiplying follower counts by a constant, reducing the pool of susceptible accounts (i.e. for account j, $\hat{F}_j = F_j(1-\eta)$). Finally, we implemented a 3-strikes rule by identifying the third incident in which a given account appeared in our full dataset. Their follower count was removed from all subsequent simulations.

Additionally, our model included a maximum value of twice the observed posts per time interval to account for a rare condition in which long-tail parameters would lead to runaway. This was observed to occur rarely enough to be challenging to quantify ($< 1\%$ of model runs), but was implemented to reduce upward bias in control conditions. This was done to ensure conservative estimates of efficacy as interventions could reduce the possibility for runaway without meaningfully impacting engagement. Such a feature would be expected in any model of a growth process with pareto-like distributions of follower counts and spread at a given time step (i.e. a negative binomial).

For the figures shown in the main text, and the tables presented in the SI, 500 simulations of all 220 events (110000 simulations per condition). For each run, we computed the cumulative engagement, and normalized it across time using linear interpolation to 20 time steps. The 100 simulations were summed across runs, from which we computed the median and credible intervals. All simulations were done in Python.

Post-event engagement

Our model cannot directly evaluate post-event engagement, as it is designed to capture viral spreading dynamics rather than long, noisy periods of posting about a topic. These periods would be difficult to capture directly with a generative model, making it challenging to infer the impact of interventions on misinformation about a topic in general. However, there exists a quite regular relationship between the proportion of posts that occur within our definition of an event and those that occur subsequent to the event (Fig 4C).

We can leverage this fact to gain insight into how interventions may impact discussion following the viral periods we analyzed. To accomplish this, we used a Bayesian log-normal regression to estimate the effect of posts within the largest event on subsequent engagement (Table S10). We then use the posterior distribution from this model to estimate subsequent engagement as a function of engagement during our simulated events with intervention. This is summed across events to generate the estimates shown in in Figure 4D. This method provides insight, but we note it is limited by the assumption that the relationship between within- and post-event engagement is invariant to interventions. Further, it is limited by the extent to which our data collection process captured posts across the entire incident (i.e. event and subsequent posts).

Code and Data Availability

Code and data to reproduce the results are available on the Open Science Foundation (https://osf.io/2dcer/).

Acknowledgements

This work was made possible through the generous support from the Knight Foundation, the University of Washington eScience Institute, and Craig Newmark Philanthropies. We also thank our collaborators, the Stanford Internet Observatory, Graphika, DFRLab, and the Electoral Integrity Partnership. We further thank Carl Bergstrom, Iain Couzin, Fernando Rossine, Rachel Moran, and Kolina Koltai for their feedback.

Author contributions statement

J.B-C., A.B., and J.W. conceived of the study. J.S., A.B., M.W., I.K., E.S., and K.S., developed the dataset. J.B-C. and J.W. wrote the model and simulation code. J.B-C. drafted the initial manuscript and all authors were involved in subsequent revision.

References

1. Velásquez, N. *et al.* Online hate network spreads malicious COVID-19 content outside the control of individual social media platforms. Tech. Rep. (2020). DOI: 10.21203/RS.3.RS-110371/V1.
2. Pennycook, G. & Rand, D. G. Research note: Examining false beliefs about voter fraud in the wake of the 2020 Presidential Election. *Harv. Kennedy Sch. Misinformation Rev.* DOI: 10.37016/mr-2020-51 (2021).
3. Election Integrity Partnership. The Long Fuse: Misinformation and the 2020 Election | Stanford Digital Repository. Tech. Rep., Center for an Informed Public, Digital Forensic Research Lab, Graphika, & Stanford Internet Observatory, Stanford Digital Repository (2021).
4. Pennycook, G. *et al.* Shifting attention to accuracy can reduce misinformation online. *Nature* 1–6, DOI: 10.1038/s41586-021-03344-2 (2021).
5. Lazer, D. M. J. *et al.* The science of fake news. *Sci. (New York, N.Y.)* **359**, 1094–1096, DOI: 10.1126/science.aao2998 (2018).
6. Whitten-Woodring, J., Kleinberg, M. S., Thawnghmung, A. & Thitsar, M. T. Poison If You Don't Know How to Use It: Facebook, Democracy, and Human Rights in Myanmar. *The Int. J. Press.* **25**, 407–425, DOI: 10.1177/1940161220919666 (2020).
7. Koltai, K. VACCINE INFORMATION SEEKING AND SHARING: HOW PRIVATE FACEBOOK GROUPS CONTRIBUTED TO THE ANTI-VACCINE MOVEMENT ONLINE. *AoIR Sel. Pap. Internet Res.* DOI: 10.5210/spir.v2020i0.11252 (2020).
8. Pennycook, G. & Rand, D. G. Fighting misinformation on social media using crowdsourced judgments of news source quality. *Proc. Natl. Acad. Sci. United States Am.* **116**, 2521–2526, DOI: 10.1073/pnas.1806781116 (2019).
9. Gollwitzer, A. *et al.* Partisan differences in physical distancing are linked to health outcomes during the COVID-19 pandemic. *Nat. Hum. Behav.* **4**, 1186–1197, DOI: 10.1038/s41562-020-00977-7 (2020).
10. Jin, F. *et al.* Epidemiological modeling of news and rumors on Twitter. In *Proceedings of the 7th Workshop on Social Network Mining and Analysis, SNA-KDD 2013*, 1–9, DOI: 10.1145/2501025.2501027 (Association for Computing Machinery, New York, New York, USA, 2013).
11. Wang, L. & Wood, B. C. An epidemiological approach to model the viral propagation of memes. *Appl. Math. Model.* **35**, 5442–5447, DOI: 10.1016/j.apm.2011.04.035 (2011).
12. Martin, T., Hofman, J. M., Sharma, A., Anderson, A. & Watts, D. J. Exploring limits to prediction in complex social systems. In *25th International World Wide Web Conference, WWW 2016*, 683–694, DOI: 10.1145/2872427.2883001 (International World Wide Web Conferences Steering Committee, Republic and Canton of Geneva, Switzerland, 2016).
13. Arif, A. *et al.* How information snowballs: Exploring the role of exposure in online rumor propagation. In *Proceedings of the ACM Conference on Computer Supported Cooperative Work, CSCW*, vol. 27, 466–477, DOI: 10.1145/2818048.2819964 (Association for Computing Machinery, 2016).

14. Kimura, M. & Saito, K. Tractable models for information diffusion in social networks. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 4213 LNAI, 259–271, DOI: 10.1007/11871637{_}27 (Springer Verlag, 2006).

15. Bakshy, E., Rosenn, I., Marlow, C. & Adamic, L. The role of social networks in information diffusion. In *WWW'12 - Proceedings of the 21st Annual Conference on World Wide Web*, 519–528, DOI: 10.1145/2187836.2187907 (ACM Press, New York, New York, USA, 2012).

16. Lloyd-Smith, J. O., Schreiber, S. J., Kopp, P. E. & Getz, W. M. Superspreading and the effect of individual variation on disease emergence. *Nature* **438**, 355–359, DOI: 10.1038/nature04153 (2005).

17. Simpson, E. & Connor, A. Fighting Coronavirus Misinformation and Disinformation - Center for American Progress. Tech. Rep., Center for American Progress (2020).

18. Bakshy, E., Mason, W. A., Hofman, J. M. & Watts, D. J. Everyone's an influencer: Quantifying influence on twitter. In *Proceedings of the 4th ACM International Conference on Web Search and Data Mining, WSDM 2011*, 65–74, DOI: 10.1145/1935826.1935845 (ACM Press, New York, New York, USA, 2011).

19. May, R. M., Levin, S. A. & Sugihara, G. Complex systems: Ecology for bankers, DOI: 10.1038/451893a (2008).

20. Levin, S. *et al.* Social-ecological systems as complex adaptive systems: Modeling and policy implications. *Environ. Dev. Econ.* **18**, 111–132, DOI: 10.1017/S1355770X12000460 (2013).

21. Carpenter, B. *et al.* Stan: A probabilistic programming language. *J. Stat. Softw.* **76**, 1–32, DOI: 10.18637/jss.v076.i01 (2017).

22. Stan Development Team. PyStan: the Python interface to Stan (2018).

23. Brady, W. J. *et al.* Emotion shapes the diffusion of moralized content in social networks. *Proc. Natl. Acad. Sci.* **114**, 7313–7318, DOI: 10.1073/pnas.1618923114 (2017).

24. Kermack, W. . & Mckendrick, A. G. A contribution to the mathematical theory of epidemics. *Proc. Royal Soc. London. Ser. A, Containing Pap. a Math. Phys. Character* **115**, 700–721, DOI: 10.1098/rspa.1927.0118 (1927).

25. Tang, L. *et al.* A Review of Multi-Compartment Infectious Disease Models. *Int. Stat. Rev.* **88**, 462–513, DOI: 10.1111/insr.12402 (2020).

26. Box, G. E. Science and statistics. *J. Am. Stat. Assoc.* **71**, 791–799, DOI: 10.1080/01621459.1976.10480949 (1976).