



FOMO (fate of online media only) in infectious disease modeling: a review of compartmental models

Joanna Sooknanan¹ · Terence A. R. Seemungal²

Received: 18 March 2022 / Revised: 5 June 2022 / Accepted: 17 June 2022
© The Author(s), under exclusive licence to Springer-Verlag GmbH Germany, part of Springer Nature 2022

Abstract

Mathematical models played a major role in guiding policy decisions during the COVID-19 pandemic. These models while focusing on the spread and containment of the disease, largely ignored the impact of media on the disease transmission. Media plays a major role in shaping opinions, attitudes and perspectives and as the number of people online increases, online media are fast becoming a major source for news and health related information and advice. Consequently, they may influence behavior and in due course disease dynamics. Unlike traditional media, online media are themselves driven and influenced by their users and thus have unique features. The main techniques used to incorporate online media mathematically into compartmental models, with particular reference to the ongoing COVID-19 pandemic are reviewed. In doing so, features specific to online media that have yet to be fully integrated into compartmental models such as misinformation, different time scales with regards to disease transmission and information, time delays, information super spreaders, the predatory nature of online media and other factors are identified together with recommendations for their incorporation.

Keywords Awareness · Media functions · Misinformation · Timescales · Superspreaders

1 Introduction

The COVID-19 pandemic has highlighted the importance of mathematical models in projecting the spread of disease outbreaks [1], in estimating epidemiological parameters [2, 3] and in evaluating the effects of various intervention or control measures [4, 5]. These models are not mere mathematical exercises—they played a central role in the decision by the government of the United Kingdom to impose a strict lockdown in March 2020 [6]. Models have generally concentrated on R_0 as the most important predictor of viral spread [7]. However, most of these models while focusing on the spread of the disease have largely ignored the impact of changes in awareness (and thus compliance with public health regulations) resulting from increased information dissemination through online media.

The ongoing COVID-19 pandemic has radically changed many aspects of our lives, especially the way in which we communicate and interact. As of January 2022, approximately 62.5 percent of the world's population was online—a 4 percent increase from the previous year [8]. Of these, 9 out of ten are engaged in social media—a 10 percent increase from the previous year [8]. Accordingly, online media such as websites, search engines and social media platforms are fast becoming major sources for news and health related information and advice [9, 10].

However, this greater access to information has also led to a greater access to misinformation, disinformation, rumors and conspiracy theories [11]—a situation which has been exacerbated by the pandemic [12]. A survey of COVID-19 misinformation on social media found that the proportion of misinformation ranged from 0.2 to 28.8% of posts [13]. With such contradictory and seemingly credible information easily available, online media can induce both positive and negative behavioral changes with regards to attitudes toward non-pharmaceutical interventions, vaccination and treatment [14, 15]. Therefore, they may influence the population's perception of the risk of infection and consequently the spread of the disease and disease dynamics [15].

✉ Joanna Sooknanan
joannasooknanan@gmail.com

¹ The University of the West Indies Open Campus, Bridgetown, Barbados

² Faculty of Medical Sciences, The University of the West Indies, St. Augustine Campus, St. Augustine, Trinidad and Tobago

Table 1 Inclusion of online media in models. For ease of comparison, the following notation is adopted—*λandy* for information transmission rate terms, S for susceptibles, E for exposed Individuals, I for infected/infectious Individuals, A for asymptomatics, R for recovered individuals and M for the media compartment

Reference	Basic Model	Effect of online media	Transmission term
[28]	SEIR	Creation of an aware class	Susceptibles interact with the media at a rate λSM to become aware, where M represents the daily normalized number of tweets about the infectious disease at any given time
[34]	SEIR	Modification of the transmission term Media-induced quarantine	The transmission rate between susceptible and infected individuals is reduced by a factor e^{-pM} due to awareness driven by media reports where p represents the weight of the media effect Terms $\lambda SM/\lambda EM$ represent the quarantine rates due to media reports
[29]	SIR	Creation of aware classes	Unaware individuals interact with the media at a rate λSM , λIM , λRM to become aware
[35]	SEI	Modification of the transmission term	The transmission rate between susceptible and infected individuals is reduced by a factor $e^{-\alpha M}$ due to awareness driven by media reports, where α is a measure of the media effect
[36]	SEIR	Creation of aware classes Modification of transmission terms	Susceptibles interact with the media at a rate λSM to become aware Asymptomatics interact with the media at a rate γAM to go into quarantine The transmission rate between susceptible and infected individuals is reduced by $\frac{M}{\rho+M}$ where ρ is a half saturation constant
[37]	SEIR	Creation of aware classes with different degrees of activity	Susceptibles interact with the media at a rate $\lambda S \frac{M}{\rho+M}$ to become aware, where ρ is a half saturation constant. Asymptomatics interact with the media at a rate $\gamma A \frac{M}{q+M}$ to go into quarantine, where q is a half saturation constant
[38]	SIRS	Creation of an aware class	Susceptibles interact with the media at a rate $\lambda S \frac{M}{K+M}$ to become aware where K is a half saturation constant
[39]	SEIR	Creation of an aware class	Susceptibles interact with the media at a rate λSM to become aware

Though there has been much research on the use of social media in the surveillance of infectious diseases [16, 17], the influence of online media (as distinct from media in general) on disease dynamics is a relatively new consideration in modeling efforts. Unlike traditional “static” media, online media (as a result of their interactivity) are themselves driven and influenced by their users and thus have emergent features

(such as such as bots, influencers and echo chambers) that are not found in traditional media. This means that their incorporation is not as straightforward as that of traditional media sources.

We review the major approaches used to incorporate online media into compartmental models, with particular reference to the ongoing COVID-19 pandemic. In doing so, we

also identify features that are specific to online media that have yet to be included in compartmental models and suggest ways of including them in modeling efforts.

2 Online media in models

Media awareness/information campaigns and their influence on human behavior have already been incorporated in models for Ebola, alcoholism, HIV, Tuberculosis and Influenza [18–24]. Aware people make behavioral changes such as mask wearing, hand-washing and avoidance of crowded places, thus reducing their risk of infection. The effects of these changes have been incorporated in models by either a reduction of the transmission term in the form of an exponential/saturated Holling type-II function [18, 20–22, 25, 26] or by the introduction of extra compartments representing awareness of the disease with [23, 26–29] and without a media compartment [30–32].

As a relatively recent form of media, few models consider social media exclusively, but instead merge them with print and broadcast media and mouth-to-mouth communication under the umbrella of awareness/information [14, 33]. Yet the extensive changes brought about by COVID-19 on the information landscape suggest that online media need to be considered as distinct entities from their traditional media counterparts. This section focuses on models that include online media exclusively—Table 1 describes their inclusion in models while Table 2 describes the associated media functions where appropriate.

3 Idiosyncratic features of online media

While the models reviewed include the effects of online media, it should be remembered that online media (in particular social media) have dramatically changed the way information is generated, consumed, and then propagated [40, 41]. Consequently, models need to be modified to accommodate emerging features arising from this novel information ecosystem. We identify four significant features and describe their incorporation (existing or potential) into traditional compartmental models.

3.1 Information, disinformation and misinformation

With so much information literally at our fingertips, it is sometimes difficult to distinguish fact from false information. Ineffective and harmful medical advice, as well as false and misleading information (negative information) undermining prevention and intervention measures may lead to increased infection and hospitalization rates by encouraging risky behavior [40–42]. In spite of this, very few infectious

Table 2 Media Functions

Reference	Media Function M
[36, 37]	$M' = r\left(1 - \frac{\theta A}{\varpi + A}\right)I - r_0(M - M_0)$, where r represents the media growth rate, θ is the decay in advertisements due to an increase in the number of aware individuals A , ϖ is a half saturation constant, M_0 is a baseline number of social media advertisements and r_0 represents the media waning rate
[34]	$M' = \eta(\delta_I I + \delta_q E_q) - \mu M$, where δ_I and δ_q are the hospitalized rates for the infected I , and the quarantined exposed E_q , η is the media reporting rate of number of newly hospitalized individuals and μ represents the media waning rate
[29]	$M' = \rho(I_1 + \theta I_2) - dM$, where ρ represents the media reporting rate, I_1 and I_2 represent infected individuals and d represents the media waning rate
[35]	$M' = \delta\left(\frac{\sigma E}{1 + h\sigma E}\right) - \mu M$, where σE represents the number of newly observed infectious individuals, δ is the media reporting rate, h is a measure of the saturation effect of media reports and μ represents the media waning rate
[38]	Information is divided into three categories: positive information M_1 (dependent on to the number of confirmed cases H), where $M'_1 = e_1 + u_1 f(H) - \mu_0 M_1$, negative information M_2 (dependent on to the number of confirmed cases H and medical resources w), where $M'_2 = e_2 + u_2 f(H) + u_3 f(w) - u_5 M_3 - \mu_0 M_2$, and policies and regulations information M_3 (which counteracts the negative information and is dependent on the total population L), where $M'_3 = u_4 f(L) - \mu_0 M_3$ μ_0 represents the media waning rate, e_i represents extra information sources, $u_i (i \neq 0)$ represents the media implementation rate and $f(x)$ refers to the amount of information generated by media coverage on variable x
[39]	$M' = \rho I - \mu M$, where ρ represents the implementation rate of the awareness programs and μ represents the media waning rate

disease models have taken negative information into account, instead focusing on the beneficial effects of information such as the reduction of contact rates or the increase in positive awareness (Table 1).

3.1.1 Including negative information and misinformation

A recent model by Chang et al. [38] recognized the importance of negative information in the modeling process by

separating information into three disparate compartments representing positive, negative and official information on policies and regulations. With dynamics similar to information release during the pandemic in response to deaths and disinformation [42], an increase in negative information (when compared to the other two types) triggered pulse conditions and the release of counteracting official information with time delay.

This is not to say that the spread of misinformation online has not been modeled. Information propagation models have been used to measure the diffusion of information, misinformation and disinformation online by comparing their spread to that of an infectious disease—analogue to a social contagion process [43–47]. These models basically adapt the traditional SIR model by dividing the population into ignorants (those not aware of the rumor—susceptibles), spreaders (those who are spreading it—infected people), and stiflers (those who know the rumor but have ceased communicating it—recovered people) [48]. Compartments may be added to incorporate the details of the spread of information via online media. For example, Maleki et al. [49] used additional compartments to include skeptics who know about the news but have decided not to spread it and exposed persons who have heard about the news but needed some time before deciding to engage in any action [49]. Also, with increasing concerns about the spread of misinformation, fact checkers who correct or debunking myths and falsehoods are playing a vital role in removing and editing information [50, 51]. They may be included in this model as a “fact checkers class,” contact with whom may result in skeptics “recovering.”

Information propagation models have been coupled with infectious disease ones to consider the effects of awareness due to information dissemination on the transmission of the disease [52–54]. The ongoing challenge is how to couple these models without resulting in an unwieldy model. A search for models coupling these two processes yielded mostly network models [53, 54] with a smaller number using compartmental models [32, 52]. However, none of these models considered the effects of negative information or included an “online media” mechanism like those in Table 1 for the spread of information. Instead, they used contact between aware and unaware people to spread awareness so that online media is not included explicitly in the model equations as in the models in Table 2.

With our increased dependence on online media for news and health related information and their subsequent influence on our behavior, this coupling between information and disease transmission and the interplay among the three types of information are important considerations and more research is needed into their inclusion in models.

3.1.2 Time scales of information and disease transmission

Social media has been a major contributor to the speed of spread of information online and a major conduit for misinformation and rumors. Most of the models reviewed assume that the spread of the epidemic and the transmission of information occur at the same time scale. However, the diffusion of information among individuals is faster than the spread of a disease and that of demographic processes [42]. By considering the time variation between information dissemination, epidemiological and demographic processes, Li et al. [35] constructed a multi-scale model describing the disease/information transmission with aware/unaware classes and a media term. Since the spread of awareness due to information dissemination is faster than population growth, the dynamical behavior of the system was analyzed using the theory of the slow-fast system [51, 55]. Despite ignoring disease related mortality, results suggested that information transmission about COVID-19 pandemic caused by media coverage can reduce the peak size of the epidemic.

Another recent study [56] comparing the spread of interacting diseases to information spread with different timescales observed that depending on the dynamics of interactions, when the diffusion of information is faster than the spread of the disease, the disease may actually have a greater prevalence and information awareness may not be as effective.

Furthermore, false information spreads more rapidly than news from reliable sources [57, 58] Though Chang et al. [38] considered the impact of positive information, negative information and information on policies and regulations on transmission, the transmission time scales were considered to be the same. For more realistic dynamics, these time scales may be further separated into a fast time scale associated with the transmission of fake news, an intermediate time scale associated with that from credible sources, and a slower time scale associated with the spread of the disease [42, 57, 58].

3.2 Time lag—time to post and react

Though information spread online appears to be instantaneous, their effects on behavior and awareness are not synchronous—there is a “pondering” time between receiving information and taking measures [58]. For this reason, the introduction of discrete time delays on models is important. These may be included in the transition from unaware to aware classes [27, 59, 60] or through a reduction in transmission rates as a response to the current media coverage [61, 62].

In addition, most of the models that include online media (Table 2) consider the growth of the media compartment to be a function dependent on the number of infected individuals.

However, in reality the information in the media compartment (whether positive, negative or official) changes as a result or reaction to numbers released earlier—often from reports from the previous day. Thus a delay may be needed to account for the time needed to respond and to organize awareness programs [59]. For this reason, a time delay may also be necessary in the media compartment [27, 59, 62, 63]. For example, Al Basir et al. (2018) used an expression of the form

$$M' = \eta\rho I(t - \tau) - \theta M \quad (1)$$

while examining the role of awareness programs on the control of infectious diseases where ρ represents disease-related deaths, θ represents the media waning rate and η is the proportionality constant which governs the implementation of awareness programs for the media compartment.

The endemic equilibrium in models with time delay exhibits Hopf-bifurcations and periodic oscillations which destabilize the system and multiple stability switches may occur with the system becoming chaotic as the time delay increases [63]. Nevertheless, including delays are important especially when modeling reported/measured data, as delays are inherent in the data gathering process [64].

3.3 Information superspreaders—Influencers, algorithms and bots

Unlike traditional “static” information sources such as newspapers, the “online information ecosystem” is especially vulnerable to manipulation [65, 66]. Not only are websites relatively simple to create and inexpensive to maintain, but online information may be rapidly disseminated (exponentially faster than humans) by computer programs—known as bots. These automated online accounts exploit the way in which content is shared and recommended—by sharing a disproportionate number of posts or by tagging or mentioning popular figures. Other rapid spreaders include social media influencers and search engine algorithms, which curate, recommend and promote content [67].

The role of information superspreaders has been recognized in modeling efforts [68–70] by distinguishing between the contact/spreading rates and the forwarding probabilities of superspreaders and normal users. Liu et al. [69] developed a susceptible users (S), superspreaders (A), normal spreaders (I) and recovered users (R) model by inserting a superspreader compartment into the classical SIR model to characterize the information propagation using Weibo data.

While traditional media may be relatively straightforward to introduce into coupled models of disease spread and information, challenges arise when bots and algorithms are considered. As primary drivers of the spread of misinformation [71], they are often overlooked—perhaps due to their

novelty and stealth like modus operandi. While we were able to find agent-based models [72], further research is needed for their incorporation into compartmental information models and thereafter into coupled models of disease transmission.

3.4 Fatigue and algorithms—another look at media functions

Table 2 describes the media functions used in the COVID-19 models, where generally the amount of media coverage/awareness is dependent on the number of people infected. In reality, this may not be the case as “pandemic fatigue” [73] becomes increasingly prevalent or other more newsworthy items take prominence [74, 75]. This means that there may be a limit to the amount of information presented, explored and absorbed by the public [76] and other forms should be considered. Li and Xiao [35] considered a saturated function of newly observed infectious individuals (Table 2) in which the media reporting rate initially rises with newly observed infections. This gradually decelerates until a plateau is reached where the media reporting rate remains constant regardless of newly observed infections similar to the Holling type 2 functional response.

A key consideration often neglected when framing media functions is the personalized, predator-like behavior of online search engines and social media algorithms which collect data and recommend content based on popularity, past behavior and the preferences of people similar to us [77]. The Internet, especially social media has become increasingly adept at creating personalized experiences for each user searching or browsing for information [77]. This content then appears in newsfeeds or search queries and may result in biased thinking and the creation of echo chambers/filter bubbles in which like-minded people reinforce each other’s opinions [67, 76–78]. These have been implicated in the growth of the anti-vax movement and vaccine hesitancy [79]. With algorithms playing a major role in the curation of content [66], they should figure prominently in the media function. A basic suggestion for their inclusion may be to consider a reproduction rate for the media compartment (rM) representing the additional coverage generated due to algorithmic recommendations.

Another suggestion may be to adapt an existing functional response from ecology to account for the predatory nature of online media. The Beddington–DeAngelis, the Crowley–Martin and the Hassell–Varley functions may be used for predator dependent functional responses [80]. For example, the Beddington–DeAngelis functional response though similar to the Holling type 2 functional response contains an extra term describing mutual interference/cooperation among predators [81]. A modification may be to use a term of the form $\frac{\sigma PS}{1+bS-cP}$ where P represents the algorithms and S the susceptibles with the extra term cP accounting for

cooperation among algorithms which may contribute to bias and polarization [82]. A challenge arises in determining P in the media function. We propose this may be done in one of two ways. If we could quantify the proportion of material posted q that accounts for algorithmic recommendations then $P = qM$. Alternatively, at the risk of violating parsimony, the media compartment may be divided into coupled compartments—representing information due to algorithmic recommendations and non-automated information.

4 Conclusions

Despite the similarity between the spread of information and the spread of infectious diseases, there are some notable differences. For example, in disease transmission every individual in contact with an infected individual has the same probability of being infected [83]. This may not be the case as long as algorithms recommend content based on viewing history [77]. Also, there is a limit to how long an individual continues to be infectious [83]. In contrast, information online may be available for an indefinite amount of time unless it is deleted. Since some articles may be reposted on other sites, even if the original site removes the post, they may still exist online and be able to exert an influence [50].

Infectious diseases, information and human behavior are inextricably linked. Unlike traditional media, information online can not only be viewed and accessed easily, but rapidly shared and discussed—this allows for a two way interaction—which may subsequently color users' attitudes, beliefs, or decisions [13, 14]. During an outbreak, the resulting changes in behavior may influence disease dynamics, especially during the early stages, where non-pharmaceutical interventions may be the only defense against spread [84]. Representing this “feedback loop between human behavior and infectious diseases is one of the key challenges in epidemiology” [83], with online media introducing yet another layer of complexity. Since R_0 is the single best predictor of disease spread [7], it would be useful to see how estimates of R_0 vary with online media input into the models.

All things considered, as online media usage increases, their unique features need to be integrated into models. This will further improve the predictive capability of the models as they become more involved in the decision making and planning processes and guide policy decisions for the containment of future outbreaks.

Authors contributions Both authors contributed to the review conception and design. Articles were collected and assessed for suitability by Terence Seemungal. The first draft of the manuscript was written by Joanna Sooknanan. Both authors read and approved the final manuscript.

Funding This research did not receive any specific grant from any funding agencies in the public, commercial, or not-for-profit sectors.

Data Availability Not applicable.

Code Availability Not applicable.

Declarations

Conflict of interest The authors (Joanna Sooknanan and Terence Seemungal) declare that there is no conflict of interest.

References

1. Khajanchi S, Sarkar K (2020) Forecasting the daily and cumulative number of cases for the COVID-19 pandemic in India. *Chaos Interdiscip J Nonlinear Sci* 30(7):071101
2. Bagal DK, Rath A, Barua A et al (2020) Estimating the parameters of susceptible-infected-recovered model of COVID-19 cases in India during lockdown periods. *Chaos Solitons Fractals* 140:110154
3. Samui P, Mondal J, Khajanchi S (2020) A mathematical model for COVID-19 transmission dynamics with a case study of India. *Chaos Solitons Fractals* 140:110173
4. Srivastav AK, Tiwari PK, Srivastava PK, Ghosh M et al (2021) A mathematical model for the impacts of face mask, hospitalization and quarantine on the dynamics of COVID-19 in India: deterministic vs. stochastic. *Math Biosci Eng* 18(1):182–213
5. Giordano G, Colaneri M, Di Filippo A et al (2021) Modeling vaccination rollouts, SARS-CoV-2 variants and the requirement for non-pharmaceutical interventions in Italy. *Nat Med* 27(6):993–998
6. Ferguson NM, Laydon D, Nedjati-Gilani, G, et al (2020). Impact of non-pharmaceutical interventions (NPIs) to reduce COVID-19 mortality and healthcare demand
7. Khajanchi S, Bera S, Roy TK (2021) Mathematical analysis of the global dynamics of a HTLV-I infection model, considering the role of cytotoxic T-lymphocytes. *Math Comput Simul* 180:354–378
8. Kemp S (2022) Digital 2022: Global Overview Report—DataReportal—Global Digital Insights. In: DataReportal. <https://datareportal.com/reports/digital-2022-global-overview-report>. Accessed 18 Mar 2022
9. Swire-Thompson B, Lazer D (2019) Public health and online misinformation: challenges and recommendations. *Annu Rev Public Health* 41:433–451
10. Bujnowska-Fedak MM, Waligóra J, Mastalerz-Migas A (2019) The internet as a source of health information and services. *Adv Exp Med Biol* 1211:1–16. https://doi.org/10.1007/5584_2019_396
11. Banerjee D, Meena KS (2021) COVID-19 as an “infodemic” in public health: critical role of the social media. *Front Public Health* 9:231
12. Allington D, Duffy B, Wessely S et al (2021) Health-protective behaviour, social media usage and conspiracy belief during the COVID-19 public health emergency. *Psychol Med* 51:1770–1770. <https://doi.org/10.1017/s0033291721000593>
13. Gabarron E, Oyeyemi SO, Wynn R (2021) Covid-19-related misinformation on social media: a systematic review. *Bull World Health Organ*. <https://doi.org/10.2471/blt.20.276782>
14. Funk S, Salathé M, Jansen VA (2010) Modeling the influence of human behaviour on the spread of infectious diseases: a Review. *J R Soc Interface* 7:1247–1256. <https://doi.org/10.1098/rsif.2010.0142>

15. Al-Dmour H, Masa'deh R, Salman A, et al (2020) Influence of social media platforms on public health protection against the COVID-19 pandemic via the mediating effects of public health awareness and behavioral changes: integrated model. *J Med Internet Res*. <https://doi.org/10.2196/19996>
16. Jordan S, Hovet S, Fung I et al (2018) Using Twitter for public health surveillance from monitoring and prediction to public response. *Data* 4:6. <https://doi.org/10.3390/data4010006>
17. Li C, Chen LJ, Chen X et al (2020) Retrospective analysis of the possibility of predicting the covid-19 outbreak from internet searches and social media data, China, 2020. *Eurosurveillance*. <https://doi.org/10.2807/1560-7917.es.2020.25.10.2000199>
18. Djiomba Njankou SD, Nyabadza F (2017) Modeling the potential role of media campaigns in ebola transmission dynamics. *Int J Diff Equ* 2017:1–13. <https://doi.org/10.1155/2017/3758269>
19. Huo H-F, Wang Q (2014) Modeling the influence of awareness programs by media on the drinking dynamics. *Abstr Appl Anal* 2014:1–8. <https://doi.org/10.1155/2014/938080>
20. Farai N, Christinah C, Zindoga M et al (2010) Analysis of an HIV/AIDS model with public-health information campaigns and individual withdrawal. *J Biol Syst* 18:357–375. <https://doi.org/10.1142/s0218339010003329>
21. Kim Y, Barber AV, Lee S (2020) Modeling Influenza Transmission Dynamics with media coverage data of the 2009 H1N1 outbreak in Korea. *PLoS One*. <https://doi.org/10.1371/journal.pone.0232580>
22. Collinson S, Heffernan JM (2014) Modeling the effects of media during an influenza epidemic. *BMC Public Health*. <https://doi.org/10.1186/1471-2458-14-376>
23. Majumder M, Tiwari PK, Pal S (2022) Impact of saturated treatments on HIV-TB dual epidemic as a consequence of COVID-19: optimal control with awareness and treatment. *Nonlinear Dyn*, 1–34
24. Das DK, Khajanchi S, Kar TK (2020) The impact of the media awareness and optimal strategy on the prevalence of tuberculosis. *Appl Math Comput* 366:124732
25. Tchuente JM, Dube N, Bhunu CP et al (2011) The impact of media coverage on the transmission dynamics of human influenza. *BMC Public Health*. <https://doi.org/10.1186/1471-2458-11-s1-s5>
26. Cui J, Sun Y, Zhu H (2007) The impact of media on the control of infectious diseases. *J Dyn Diff Equat* 20:31–53. <https://doi.org/10.1007/s10884-007-9075-0>
27. Greenhalgh D, Rana S, Samanta S et al (2015) Awareness programs control infectious disease—multiple delay induced mathematical model. *Appl Math Comput* 251:539–563. <https://doi.org/10.1016/j.amc.2014.11.091>
28. Kumar S, Xu C, Ghildayal N et al (2021) Social media effectiveness as a humanitarian response to mitigate influenza epidemic and covid-19 pandemic. *Ann Oper Res*. <https://doi.org/10.1007/s10479-021-03955-y>
29. Li T, Xiao Y (2021) Linking the disease transmission to information dissemination dynamics: an insight from a multi-scale model study. *J Theor Biol* 526:110796. <https://doi.org/10.1016/j.jtbi.2021.110796>
30. Agaba GO, Kyrychko YN, Blyuss KB (2017) Mathematical model for the impact of awareness on the dynamics of infectious diseases. *Math Biosci* 286:22–30. <https://doi.org/10.1016/j.mbs.2017.01.009>
31. Funk S, Gilad E, Jansen VAA (2010) Endemic disease, awareness, and local behavioural response. *J Theor Biol* 264:501–509. <https://doi.org/10.1016/j.jtbi.2010.02.032>
32. Musa SS, Qureshi S, Zhao S et al (2021) Mathematical modeling of covid-19 epidemic with effect of awareness programs. *Infect Disease Model* 6:448–460. <https://doi.org/10.1016/j.idm.2021.01.012>
33. Rai RK, Tiwari PK, Kang Y, Misra AK (2020) Modeling the effect of literacy and social media advertisements on the dynamics of infectious diseases. *Math Biosci Eng* 17(5):5812–5848
34. Zhou W, Wang A, Xia F et al (2020) Effects of media reporting on mitigating spread of covid-19 in the early phase of the outbreak. *Math Biosci Eng* 17(3):2693–2707
35. Li T, Xiao Y (2021) Complex Dynamics of an epidemic model with saturated media coverage and recovery. *Nonlinear Dyn*. <https://doi.org/10.21203/rs.3.rs-644391/v1>
36. Rai RK, Khajanchi S, Tiwari PK et al (2021) Impact of social media advertisements on the transmission dynamics of COVID-19 pandemic in India. *J Appl Math Comput* 68:19–44. <https://doi.org/10.1007/s12190-021-01507-y>
37. Tiwari RK, Rai RK, Khajanchi S et al (2021) Dynamics of coronavirus pandemic: effects of community awareness and global information campaigns. *Eur Phys J Plus*. <https://doi.org/10.1140/epjp/s13360-021-01997-6>
38. Chang X, Wang J, Liu M et al (2021) Study on an SIHRS model of COVID-19 pandemic with impulse and time delay under media coverage. *IEEE Access* 9:49387–49397. <https://doi.org/10.1109/access.2021.3064632>
39. Lacitignola D, Saccomandi G (2021) Managing awareness can avoid hysteresis in disease spread: an application to coronavirus covid-19. *Chaos Solitons Fractals* 144:110739. <https://doi.org/10.1016/j.chaos.2021.110739>
40. Tsao S-F, Chen H, Tisseverasinghe T et al (2021) What social media told us in the time of covid-19: a scoping review. *Lancet Digital Health*. [https://doi.org/10.1016/s2589-7500\(20\)30315-0](https://doi.org/10.1016/s2589-7500(20)30315-0)
41. Du E, Chen E, Liu J, Zheng C (2021) How do social media and individual behaviors affect epidemic transmission and control? *Sci Total Environ* 761:144114. <https://doi.org/10.1016/j.scitotenv.2020.144114>
42. Cinelli M, Quattrociocchi W, Galeazzi A et al (2020) The COVID-19 social media infodemic. *Sci Rep*. <https://doi.org/10.1038/s41598-020-73510-5>
43. Zhao L, Cui H, Qiu X et al (2013) Sir rumor spreading model in the new media age. *Physica A* 392:995–1003. <https://doi.org/10.1016/j.physa.2012.09.030>
44. Yin F, Shao X, Ji M, Wu J (2021) Quantifying the influence of delay in opinion transmission of covid-19 information propagation: modeling study. *J Med Internet Res*. <https://doi.org/10.2196/25734>
45. Yin F, Lv J, Zhang X et al (2020) Covid-19 information propagation dynamics in the Chinese sina-microblog. *Math Biosci Eng* 17:2676–2692. <https://doi.org/10.3934/mbe.2020146>
46. Abdullah S, Wu X (2011) An epidemic model for news spreading on Twitter. 2011 IEEE 23rd International Conference on Tools with Artificial Intelligence. <https://doi.org/10.1109/ictai.2011.33>
47. Shrivastava G, Kumar P, Ojha RP et al (2020) Defensive modeling of fake news through online social networks. *IEEE Trans Comput Social Syst* 7:1159–1167. <https://doi.org/10.1109/tcss.2020.3014135>
48. Daley DJ, Kendall DG (1964) Epidemics and rumours. *Nature* 204:1118–1118. <https://doi.org/10.1038/2041118a0>
49. Maleki, M, Arani M, Buchholz E, et al (2021) Applying an epidemiological model to evaluate the propagation of misinformation and legitimate COVID-19-related information on twitter. In *International Conference on Social Computing, Behavioral-Cultural Modeling and Prediction and Behavior Representation in Modeling and Simulation* (pp. 23–34). Springer, Cham
50. Ball P, Maxmen A (2020) The epic battle against coronavirus misinformation and conspiracy theories. *Nature* 581:371–374. <https://doi.org/10.1038/d41586-020-01452-z>
51. Venegas-Vera AV, Colbert GB, Lerma EV (2020) Positive and negative impact of social media in the COVID-19 era. *Rev Cardiovasc Med* 21:4
52. Kabir KMA, Kuga K, Tanimoto J (2019) Analysis of sir epidemic model with information spreading of awareness. *Chaos Solitons Fractals* 119:118–125. <https://doi.org/10.1016/j.chaos.2018.12.017>

53. Zhan X-X, Liu C, Zhou G et al (2018) Coupling dynamics of epidemic spreading and information diffusion on complex networks. *Appl Math Comput* 332:437–448. <https://doi.org/10.1016/j.amc.2018.03.050>
54. Funk S, Gilad E, Watkins C, Jansen VA (2009) The spread of awareness and its impact on epidemic outbreaks. *Proc Natl Acad Sci* 106:6872–6877. <https://doi.org/10.1073/pnas.0810762106>
55. Feng Z, Velasco-Hernandez J, Tapia-Santos B (2013) A mathematical model for coupling within-host and between-host dynamics in an environmentally-driven infectious disease. *Math Biosci* 241:49–55. <https://doi.org/10.1016/j.mbs.2012.09.004>
56. Ventura PC, Moreno Y, Rodrigues FA (2021) Role of time scale in the spreading of asymmetrically interacting diseases. *Phys Rev Res* 3(1):013146
57. Obiała J, Obiała K, Mańczak M et al (2021) Covid-19 misinformation: Accuracy of articles about coronavirus prevention mostly shared on social media. *Health Policy Technol* 10:182–186. <https://doi.org/10.1016/j.hlpt.2020.10.007>
58. Vosoughi S, Roy D, Aral S (2018) The spread of true and false news online. *Science* 359(6380):1146–1151
59. Basir FA, Ray S, Venturino E (2018) Role of media coverage and delay in controlling infectious diseases: a mathematical model. *Appl Math Comput* 337:372–385. <https://doi.org/10.1016/j.amc.2018.05.042>
60. Agaba GO, Kyrychko YN, Blyuss KB (2017) Dynamics of vaccination in a time-delayed epidemic model with awareness. *Math Biosci* 294:92–99. <https://doi.org/10.1016/j.mbs.2017.09.007>
61. Zhao H, Lin Y, Dai Y (2014) An SIRS epidemic model incorporating media coverage with Time Delay. *Comput Math Methods Med* 2014:1–10. <https://doi.org/10.1155/2014/680743>
62. Song P, Xiao Y (2019) Analysis of an epidemic system with two response delays in media impact function. *Bull Math Biol* 81:1582–1612. <https://doi.org/10.1007/s11538-019-00586-0>
63. Misra AK, Rai RK, Tiwari PK, Martcheva M (2021) Delay in budget allocation for vaccination and awareness induces chaos in an infectious disease model. *J Biol Dyn* 15:395–429. <https://doi.org/10.1080/17513758.2021.1952322>
64. Guglielmi N, Iacomini E, Viguier A (2021) Identification of time delays in covid-19 data, arXiv preprint [arXiv:2111.13368](https://arxiv.org/abs/2111.13368)
65. Shao C, Ciampaglia GL, Varol O et al (2018) The spread of low-credibility content by Social Bots. *Nat Commun*. <https://doi.org/10.1038/s41467-018-06930-7>
66. Himelein-Wachowiak MK, Giorgi S, Devoto A et al (2021) Bots and misinformation spread on social media: A mixed scoping review with implications for covid-19. *J Med Internet Res*, 23(5)
67. Cinelli M, De Francisci MG, Galeazzi A et al (2021) The Echo Chamber Effect on social media. *Proc Natl Acad Sci*. <https://doi.org/10.1073/pnas.2023301118>
68. Yin F, Xia X, Song N et al (2020) Quantify the role of super-spreaders -opinion leaders- on covid-19 information propagation in the Chinese sina-microblog. *PLoS One*. <https://doi.org/10.1371/journal.pone.0234023>
69. Liu Y, Wu B, Wang B (2015) Characterizing super spreading in microblog: an epidemic-based model. 2015 IEEE International Conference on Big Data (Big Data). <https://doi.org/10.1109/bigdata.2015.7364020>
70. Zenk L, Steiner G, Pina e Cunha M et al (2020) Fast response to superspreading: uncertainty and complexity in the context of covid-19. *Int J Environ Res Public Health* 17:7884. <https://doi.org/10.3390/ijerph17217884>
71. Ayers JW, Chu B, Zhu Z et al (2021) Spread of misinformation about face masks and COVID-19 by automated software on Facebook. *JAMA Intern Med* 181:1251. <https://doi.org/10.1001/jamainternmed.2021.2498>
72. Lotito QF, Zanella D, Casari P (2021) Realistic aspects of simulation models for fake news epidemics over social networks. *Future Internet* 13:76. <https://doi.org/10.3390/fi13030076>
73. Reicher S, Drury J (2021) Pandemic fatigue? How adherence to covid-19 regulations has been misrepresented and why it matters. *BMJ*. <https://doi.org/10.1136/bmj.n137>
74. Islam AN, Laato S, Talukder S, Sutinen E (2020) Misinformation sharing and social media fatigue during COVID-19: an affordance and cognitive load perspective. *Technol Forecast Soc Chang* 159:120201. <https://doi.org/10.1016/j.techfore.2020.120201>
75. Pearman O, Boykoff M, Osborne-Gowey J et al (2021) Covid-19 media coverage decreasing despite deepening crisis. *Lancet Planetary Health*. [https://doi.org/10.1016/s2542-5196\(20\)30303-x](https://doi.org/10.1016/s2542-5196(20)30303-x)
76. Schmidt AL, Zollo F, Del Vicario M et al (2017) Anatomy of news consumption on Facebook. *Proc Natl Acad Sci* 114:3035–3039. <https://doi.org/10.1073/pnas.1617052114>
77. Perra N, Rocha LE (2019) Modeling opinion dynamics in the age of algorithmic personalisation. *Sci Rep* 9(1):1–11
78. Spohr D (2017) Fake news and ideological polarization. *Bus Inf Rev* 34:150–160. <https://doi.org/10.1177/0266382117722446>
79. Burki T (2020) The online anti-vaccine movement in the age of covid-19. *Lancet Digital Health*. [https://doi.org/10.1016/s2589-7500\(20\)30227-2](https://doi.org/10.1016/s2589-7500(20)30227-2)
80. Skalski GT, Gilliam JF (2001) Functional responses with predator interference: viable alternatives to the holling type II model. *Ecology* 82:3083–3092. [https://doi.org/10.1890/0012-9658\(2001\)082\[3083:frwpiv\]2.0.co;2](https://doi.org/10.1890/0012-9658(2001)082[3083:frwpiv]2.0.co;2)
81. Beddington JR (1975) Mutual interference between parasites or predators and its effect on searching efficiency. *J Anim Ecol* 44:331. <https://doi.org/10.2307/3866>
82. Wölker A, Powell TE (2021) Algorithms in the newsroom? News readers' perceived credibility and selection of automated journalism. *Journalism* 22(1):86–103
83. Martcheva M (2015) Introduction to mathematical epidemiology. Springer, New York
84. Perra N (2021) Non-pharmaceutical interventions during the COVID-19 pandemic: a review. *Phys Rep* 913:1–52. <https://doi.org/10.1016/j.physrep.2021.02.001>