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Comparing models of online misinformation distribution: A survey paper

Zhengyao Liew, *Lambert High School, Georgia, USA, zyliew7@gmail.com*
Xin Tian, *Kennesaw State University, Georgia, USA, xtian2@kennesaw.edu*
Zhigang Li, *Kennesaw State University, Georgia, USA, zli8@kennesaw.edu*

Abstract

The rapid dissemination of misinformation has become one of the most pressing issues of the modern world, as social media platforms enable misinformation to be spread incredibly quickly and unpredictably. To combat the misinformation epidemic, many misinformation models have been developed to simulate and study the spread of misinformation so that it may be understood and mitigated more effectively. While many survey papers review misinformation holistically, there is a gap in the literature for a survey of models in particular, mainly because the field is still relatively young. To overcome this gap, we compile a dataset of 28 papers, each using its model to study misinformation. In reviewing trends amongst these models, we find that a. there is a shortage of papers that evaluate countermeasures against misinformation or take their influence into account, and b. platforms other than Twitter/X are underused as sources for model validation data, considering their real-world importance.

Keywords: misinformation modelling, misinformation, digital misinformation, social media, agent-based modelling

Introduction

The spread of misinformation has become one of the most pressing issues of the 21st century, primarily being propagated through the internet. As social media and internet use have increased over the last decade, the amount of misinformation spread through the internet has grown proportionally. However, misinformation poses a dangerous threat to society. In the past few years, for example, digital misinformation increased COVID-19 vaccine hesitancy in the United States (Crouse & Dupuis, 2022), creating a difficult challenge for the US healthcare system. Even in a broader sense, online misinformation erodes the population's general trust in institutions such as the federal government and national news media (Boulianne & Humprecht, 2023). The threat is compounded further by the rapid growth of the internet, which has exponentially increased the reach of individuals and organizations that seek to spread misinformation, enabling the crisis to reach a global scale.

Unsurprisingly, combatting the misinformation crisis has posed several challenges; Misinformation spreads in an inherently unpredictable manner and has proven difficult to regulate systematically. Regulating online content poses optics problems for social media platforms and becomes increasingly difficult as lines between reality and fiction blur in different political groups. Furthermore, the sheer scale of the problem necessitates extremely generalizable solutions that are still viable on a case-by-case basis. Despite the

complexity of the problem, solutions are still possible. In the past decade, a growing body of literature surrounding methods to mitigate the spread of misinformation online has become established as a field in itself. Thus, there is an urgent need for accurate and practical methods to model misinformation. Misinformation models enable researchers to understand the nature of this phenomenon better and predict its spread so that it may be countered more efficiently. Indeed, models for misinformation have been designed for a wide variety of use cases. The present paper provides a holistic analysis of this field. Section 2 reviews the state of misinformation modeling and summarizes trends in the field. Section 3 concludes with a discussion of the work and opportunities for future research.

Literature Review

Misinformation models are primarily used to generalize the nature of online misinformation. While they model the same phenomena, they use various approaches and techniques to emphasize aspects of online misinformation and simulate it in different environments. As a result, while there is no single 'best' model that perfectly captures all aspects of misinformation spread, a large number of models are still useful in the study of misinformation.

Holistically speaking, we find a lack of papers directly comparing these models against each other. There is a large body of survey papers reviewing misinformation on a general level (Aïmeur et al., 2023; Suarez-Lledo & Alvarez-Galvez, 2021; Zhou et al., 2023) as well as a large body of papers reviewing methods for detecting misinformation (Bondielli & Marcelloni, 2019; Islam et al., 2020; Su et al., 2020), but very few such works exist for the misinformation modeling field in particular. However, a targeted analysis comparing the most popular trends in modeling is critical for determining which methods should be pursued further. By summarizing specific trends in model development, we hope to provide a general understanding of the field today and identify opportunities for future growth in the field. To streamline this survey paper, we stratify two key research questions to construct a framework that can point the way for future research within misinformation modeling.

1. *What are the most popular trends in the field?*
2. *Which trends have the most significant gaps in the field?*

To answer these questions, we first identify which trends we seek to explore. Since most models utilize a combination of several techniques (e.g. natural language processing and graph theory) and it also is not clear in many cases what the primary method or framework being used is, we allow for the same paper to be classified under more than a single "trend" in our review. In doing so, we can gain a much more accurate understanding of the true prevalence of any given trend.

While many model features overlap between different models, the majority fit into one of two categories: Agent-based or graph-based models. Agent-based models (ABM) consider each user as an individual actor, simulating real social media platforms by ascribing various traits and actions to users. On the other hand, graph-based models take a more abstract approach by condensing a large group of users into a graph, within which each individual is represented as a node, and each edge represents a connection between two individuals. These two approaches are particularly useful in the analysis of the literature because not only are they mutually exclusive, but nearly all models fall into one or the other. However, they are not the only recurring themes in misinformation models. The literature review will isolate individual trends within the field so that each may be analyzed properly.

Model Categories

Agent-based Models

Agent-based modeling was originally developed as an easier way to build computer animations consisting of large groups of individual actors (Reynolds, 1987), but the method has come to play a key role in modeling misinformation. Agent-based models are the most varied of the model types, as what constitutes an "agent" has no standard definition. These models also implement a large range of other concepts, such as Bayesian probability (Acemoglu et al., 2021) and Game Theory (Kopp et al., 2018).

Graph-Based Models and Greedy Algorithms

Graph-based misinformation models represent large groups of users as a single graph made up of nodes representing users and edges representing the relationships between them. While the term "graph-based model" is rarely used in literature, we categorize any model that utilizes nodes and edges as an abstraction of users and their relations as a graph-based model. A greedy algorithm is one that always takes the locally optimal choice at each stage of a simulation. Within graphs, greedy algorithms are implemented so that the amount of misinformation spread is maximized at each step of the simulation process (Tanınmış et al., 2020; Zhu et al., 2021)

Epidemiological Models and Countermeasure Integration

Epidemiological models use the spread of infectious diseases as a proxy to represent the spread of misinformation online. While there are minor differences in implementation, epidemiological models are similar in that misinformation within them spreads exponentially from a larger and larger host population of people who have been misinformed. This structure is similar to that of real-world misinformation spread, as it represents the core of what makes misinformation such a pressing threat: The ease with which it can be quickly spread online (Rastogi, 2022). Countermeasures against misinformation take a variety of forms, from fact-checking on posts to simulations of blocking users. Evaluating countermeasures is a vital application of misinformation models, as the findings of these papers are prescriptive instead of descriptive, contributing to their real-world utility.

Empirical Validation via Twitter, Facebook, Covid-10, and Elections

Twitter is infamous for its algorithm's ability to spread information quickly and construct impenetrable echo chambers for users. Twitter's content is nearly entirely text, making the construction of datasets using tweets significantly more accessible than on other platforms, where multimedia posts are more common. Considering this, in addition to the nature of the platform's recommendation algorithm, it is a particularly viable option for building datasets. Facebook is particularly relevant to solving the spread of misinformation worldwide. Its administration has also come under more criticism than any other platform for perpetuating misinformation globally, largely because of the company's visibility.

The COVID-19 pandemic has been one of the most significant empirics demonstrating the real-world impacts of online misinformation, particularly regarding the increase of vaccine hesitancy in the US because of online misinformation (Crouse & Dupuis, 2022). Because of its recency, there is also a wealth of well-recorded data to pull from for datasets using COVID-19 misinformation. Conspiracy theories related to US presidential elections are among the most widespread on social media and have, consequently, become

the most studied in misinformation modeling. Election misinformation erodes general trust in government institutions, changes voter behavior, and discourages civic participation (Cantarella et al., 2023).

Methodology

We analyze 28 papers for this literature review, each of which uses the modeling of misinformation spread to study online misinformation. We first begin our research process by filtering sources through Google Scholar. We use several criteria to decide which sources are valid for our review. First, we exclude sources from non-reputable journals or otherwise non-academic sources, as they are much more challenging to validate and do not represent the development of misinformation modeling within academia. Second, we broadened the scope of our search beyond papers with the word "misinformation model" as a keyword. Instead, we analyze the methodology sections of the papers, studying various aspects of misinformation to determine whether a model is used to determine the results. Finally, we solely observe papers published within the last decade, as our goal is only to find recent developments and changes in the misinformation modeling field, not to trace a complete history of all misinformation models.

Utilizing the above criteria, we found 28 papers using some form of modeling to study misinformation through Google Scholar. Beyond simply classifying them as misinformation models, we identified recurring themes between these papers, noting which papers mentioned or utilized these themes. Finally, we take note of specific implementations of each technique or trend and any further nuances within the particular paper.

Results

Using the 28 papers we found as a representative dataset of the entire misinformation modeling field, we answered the two previously yielded questions.

1. What are the most popular trends in the field?

The trends present in each paper are displayed in Table 1 below. However, in order to fully evaluate popularity, we not only analyze the number of articles that fall under each trend, but also the amount of citations for each said article as a proxy for the amount of influence the article has had on the field. With these two factors into account, we make 3 key findings in terms of popularity.

First, despite the emergence of a few outlying model types, such as the epidemiological model or the implementation of greedy algorithms, it is clear that graph-based and agent-based models have been and continue to be the two most dominant model types. While graph-based models (57% of all models) have a slight edge over their agent-based counterparts (43% of all models), both continue to be viable options in the field, even today.

Second, in terms of model validation, Twitter holds a dominant lead as the go-to for validation data. It is used in 45% of all papers with some form of model validation, a significant portion compared to Facebook's 13% at second place. This is for a number of reasons, including it's approachable (and formerly free) API, as well as the text-based nature of most content on the platform. However, having such a large portion of models be validated from only Twitter datasets could raise questions about the generalization of these

findings to other platforms. Third, since the COVID-19 pandemic, COVID-19 misinformation has overtaken election misinformation as the most popular topics of posts for validation datasets. The disproportionate focus on COVID-19 is warranted, however, as vaccine misinformation has directly contributed to increased death rates in the US, making the problem a pressing matter.

2. Which trends have the most significant gaps in the field?

While some models attempt to break the mold and explore new avenues of research within the misinformation modelling field, most stay within the few trends listed above. As such, there are a number of trends that have been touched on in the field, but could significantly benefit from further exploration.
First, the influence of countermeasures against misinformation could be integrated into more misinformation models. While most papers only make descriptive conclusions about qualities of misinformation (such as the repeated conclusion that a small minority of actors spread the majority of misinformation), models which evaluate countermeasures make new findings that can be applied to real social media platforms. However, only 14% of models integrate countermeasures in their simulations.

Second, platforms beyond Twitter/X could be used more often for model validation datasets. Twitter's relevance within the misinformation modelling field is disproportionate to it's relevance to the real misinformation epidemic. While the platform is by far the most popular source of model validation data, Facebook, Youtube, and Instagram are far more popular as platforms, with multiple times more users each (Dixon, 2024). However, these platforms are far behind Twitter in terms of datasets, only having been used in 3, 1, and 2 papers respectively (Displayed in Table 2 below). However, it should be noted that these platforms are significantly less centered around text than Twitter, and thus could pose their own unique problems in processing a larger proportion of multimedia posts.

Table 1: Model Type Trends

	Agent-Based Model	Graph-Based Model	Greed Algorithm	Epidemiological Model	Countermeasure
(Acemoglu et al., 2021)	**X**				
(Apuke & Omar, 2021)	**X**				
(Bodaghi & Oliveira, 2022)		**X**			
(Brody & Meier, 2018)	**X**				
(Del Vicario et al., 2016)		**X**			
(Franceschi & Pareschi, 2022)		**X**		**X**	
(Gausen et al., 2023)	**X**			**X**	**X**
(Jiang et al., 2023)		**X**			
(Kopp et al., 2018)	**X**				
(Maleki et al., 2021)		**X**		**X**	
(Manouchehri et al., 2021)	**X**		**X**		**X**

	Agent-Based Model	Graph-Based Model	Greed Algorithm	Epidemiological Model	Countermeasure
(Mostagir & Siderius, 2023)	X				
(Murayama et al., 2021)		X	X		
(Pourghomi et al., 2018)	X				X
(Puri et al., 2024)	X			X	
(Rastogi, 2022)		X		X	
(Ruiz-Frau et al., 2020)		X			
(Scholz et al., 2017)	X				
(Schroeder et al., 2021)		X			
(Shrivastava et al., 2020)		X			X
(Sikder et al., 2020)	X				
(Sobkowicz & Sobkowicz, 2021)	X			X	
(Sulis & Tambuscio, 2020)		X			
(Tambuscio et al., 2018)		X			
(Tambuscio et al., 2018)		X			
(Tanınmış et al., 2020)		X	X		
(Törnberg, 2018)		X		X	
(Zhu et al., 2021)		X	X		

Table 2. Empirical Validation Trends

Dataset Source	Number of Paper	Dataset Topic	Number of Papers
Twitter	10	**COVID-19**	6
Facebook	3	**Elections**	4
Other	9	**Other**	13
No Model Validation	6	**No Model Validation**	6

Discussion

While misinformation modeling holds massive potential as a critical tool in combatting the global misinformation epidemic, much of this potential needs to be harnessed with current model iterations. Many papers we find need to be more varied and come to similar conclusions about the nature of misinformation with similar models to reach those conclusions. As a result, we suggest branching out into more

experimental model types and developing more varying datasets to validate these models so that their accuracy and generalization can be maximized. We would also recommend hybrid models as a potential for innovation, instead of the current stratified trends identified in the tables above.

Unfortunately, this survey is fairly limited in scope due to the relatively small size of the misinformation modelling field and the strict parameters applied while identifying viable sources. Future literature reviews could expand the scope of sources that are analyzed, or include more works related to misinformation beyond modelling. Despite these shortcomings, the present paper still provides a general understanding of the current state of misinformation modelling and where its future could lead.

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