



Review article

The physics of news, rumors, and opinions

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ABSTRACT

The boundaries between physical and social networks have narrowed with the advent of the Internet and its pervasive platforms. This has given rise to a complex adaptive information ecosystem where individuals and machines compete for attention, leading to emergent collective phenomena. The flow of information in this ecosystem is often non-trivial and involves complex user strategies—from the forging or strategic amplification of manipulative content to large-scale coordinated behavior—that trigger misinformation cascades, echo-chamber reinforcement, and opinion polarization. We argue that statistical physics provides a suitable and necessary framework for analyzing the unfolding of these complex dynamics on socio-technological systems. This review systematically covers the foundational and applied aspects of this framework. The review is structured to first establish the theoretical foundation for analyzing these complex systems, examining both structural models of complex networks and physical models of social dynamics (e.g., epidemic and spin models). We then ground these concepts by describing the modern media ecosystem where these dynamics currently unfold, including a comparative analysis of platforms and the challenge of information disorders. The central sections proceed to apply this framework to two central phenomena: first, by analyzing the collective dynamics of information spreading, with a dedicated focus on the models, the main empirical insights, and the unique traits characterizing misinformation; and second, by reviewing current models of opinion dynamics, spanning discrete, continuous, and coevolutionary approaches. In summary, we review both empirical findings based on massive data analytics and theoretical advances, highlighting the

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valuable insights obtained from physics-based efforts to investigate these phenomena of high societal impact.

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1. Introduction

The study of social systems has long been approached by the definition of frameworks from economics, psychology, and sociology, which often focus on individual decision-making or qualitative interactions. However, many large-scale social phenomena such as opinion dynamics, crowd behavior, market fluctuations, and migration patterns exhibit emergent properties that bear striking resemblance to the collective behavior of complex physical systems [1]. This suggests a deeper analogy: some feature in the behavior of human populations may be modeled as many-body systems governed by statistical mechanics, where macroscopic social patterns arise from microscopic interactions between individuals (often not represented by an ordered lattice structure, but rather by complex graphs [2]), much like how temperature and pressure emerge from molecular collisions. In this sense, the boundaries between physical and social networks have narrowed since the advent of the Internet, with platforms such as social media and portable devices allowing real-time access to news everywhere on Earth.

In the last decades, the massive use of information and communication technologies (ICT) is producing a continuous large flow of traceable data that can be used to describe and understand the changes in our society, from an individual level to collectives [3–7]. The complexity of this analysis calls for an approach that, on the example of statistical physics, can lead to a properly defined physics of society [8], describing society through its interacting individuals. In this respect, the quantities of interest come from sociometric and behavioral data [9], covering several aspects of human dynamics, from mobility to communication. Nevertheless, it is unlikely that such quantities can be statistically described using the same approaches adopted for large sets of particles—like in a box filled with gas—to obtain the equivalent of a Maxwell–Boltzmann distribution. This is because individuals are more similar to active matter than gas particles and that groups of individuals—with their interactions—are best described by fat-tail distributions [10–17] and out-of-equilibrium dynamics [18–23]. On this rugged landscape, we must, therefore, stick to the few observational regularities—such as scaling laws—that we can uncover on this extremely heterogeneous structure given by individuals and their social networks.

Statistical physics provides a natural toolkit for understanding such systems. By treating individuals as interacting particles subject to social forces (e.g., peer influence, cultural norms, or economic incentives), we can apply concepts like phase transitions, entropy, and stochastic dynamics to explain phenomena such as polarization, consensus formation, or sudden shifts in public opinion. For instance:

- Phase transitions may describe abrupt societal changes (e.g., revolutions or market crashes) as critical points where small perturbations trigger system-wide transformations.
- Diffusion processes can model the spread of information or behaviors through social networks, analogous to heat propagation in materials.
- Entropic forces might quantify the role of randomness in decision-making, where a suitable definition of “social temperature” reflects the variability of individual choices.

This paper explores how methods from statistical physics including agent-based models, mean-field theories, and non-equilibrium thermodynamics can shed light on social dynamics. We argue that such an approach offers two key advantages:

Quantitative predictability By identifying appropriate parameters and laws, we can forecast large-scale trends from local interaction rules. That is, we can identify order parameters (e.g., the average belief polarization of a population) and scaling laws that govern phase transitions. This allows us to move beyond anecdotal observation and forecast large-scale trends, such as the viral tipping point of a false narrative, directly from the local rules of user engagement, algorithmic amplification, and homophily.

Universality Social systems may belong to the same universality classes as physical systems, enabling cross-disciplinary insights. The patterns of misinformation emergence, persistence, and decay may not be unique to social systems. Instead, they might belong to the same universality classes as established physical systems, such as the spontaneous magnetization in ferromagnetic materials or the activation dynamics in chemical reaction networks. This universality enables powerful cross-disciplinary insights, allowing us to adapt well-understood physical models to predict how misinformation will behave under different network topologies or moderation policies. Ultimately, by treating misinformation as a collective phenomenon emerging from micro-level interactions, statistical physics provides a rigorous, mathematically grounded toolkit to diagnose vulnerabilities, simulate intervention strategies, and potentially control the “epidemiology” of false information in digital ecosystems.

Challenges remain, of course. Human behavior introduces complexities like memory, strategic intent, and heterogeneous interactions, which lack direct physical analogs. Yet, by adapting tools from active matter physics and disordered systems [24] with evolutionary game theory, we may bridge these gaps. Ultimately, this framework aims to unify disparate social phenomena appearing in different disciplines [25] under the lens of statistical mechanics, revealing the "thermodynamics of society" and offering new levers for policy design [8].

In this review, we shall describe the efforts to analyze this process through a complex network-based approach, since this seems to be a natural choice for modeling the structure and dynamics of a complex society which is interconnected at both individual and group levels. We justify this statement based on the definition of complexity, that is, the emergence of a new behavior whenever the number of ingredients (the particles, the agents, whatever describes the system under consideration) becomes very large [1,26–29]. Since complex systems are defined by system composed by many interacting parts, not surprisingly complex networks [30] appear as the simplest mathematical model able to capture a variety of typical features quantitatively [24]. Complex networks have gained an increasing amount of consideration to be an optimal integration and investigation tool for real-world systems of diverse fields, from biology [31,32], to finance [33,34], from technology [35,36] to sociology [19]. Many of these systems show particular behaviors that distinguish them from other traditional systems, such as their scale-free nature, the emergence of power-law degree distributions and small-world phenomenon [37–39], the co-existence of several contexts—usually named layers—of interaction [40–43] and interdependency [44,45] (see [46,47] for a recent review). Even if incredibly complex, a representation based on static interactions is still insufficient to explain information spreading and evolution in an interconnected society. On the one hand, even the structure of social systems changes dynamically and exhibits time-varying behavior to be accounted for [48–51], with non-trivial memory effects [52,53]. On the other hand, one has to consider that the sites of the networks (e.g., users in a socio-technical system) are active, so they can rearrange their links, join new groups, unfollow people and decide what to share, how and when [21], leading non-trivial collective behaviors [54–57]. Given such a broad and heterogeneous phenomenology, the activity of a node is a game-changer even in simple spreading models. An emblematic example is given by the mobility of active matter when sites are left free to explore their environment [58], and diffusion is characterized by a smaller dynamical exponent [59] than the one we could expect on a network [60].

1.1. Aims and scope

The core goal of this review is to illuminate the principles governing the collective social dynamics of information and opinions and demonstrate how models and techniques rooted in statistical physics and network science provide the essential framework to achieve this understanding. Specifically, this paper addresses the following intertwined objectives that span structure, dynamics, and societal impact.

Understanding the structure and dynamics of socio-technical systems

Online social platforms have become pervasive communication channels, where decentralized individual interactions drive complex, out-of-equilibrium dynamics. The process of news creation, diffusion, and opinion formation now occurs on highly disordered, active media where individuals and automated accounts (active units) initiate, terminate, or modify the flow of information.

The challenge lies in quantifying the impact of this systemic shift. We aim to clarify:

1. **How and how fast do news, rumors, and opinions spread?** We seek to establish quantitative models that capture the dynamics of complex contagion and non-linear interactions characteristic of these systems.
2. **What are the fundamental physical and network mechanisms governing spread?** This involves investigating the principles at the basis of spreading patterns in disordered structures and quantifying the pervasiveness of different narratives, from simple viral cascades to complex behavioral adoption.

Characterizing the role of network topology and user behavior

Social platforms are effectively complex networks where users (nodes) and their interactions (edges) encode the pathways for information flow. These networks exhibit highly heterogeneous connectivity, often characterized by fat-tailed degree distributions and significant mesoscale organization (clustering, communities, and homophily).

To understand reach and virality, we must characterize:

3. **What network features and user behaviors govern reach, virality, and threshold effects?** We will explore how topological features (e.g., directionality, weighting, community structure) interact with microscopic user-level dynamics (e.g., cognitive biases, attention allocation, reinforcement) to determine macroscopic outcomes. This calls for the use of rigorous methods, such as null models, to isolate the structural properties driving observed dynamics.

Modeling collective phenomena: consensus, polarization, and fragmentation

At the collective level, the interplay between structure and individual behavior gives rise to critical emergent phenomena. Interactions driven by homophily often create tightly-knit, ideologically insulated communities like echo chambers and polarized communities.

A central objective is to model and explain these collective states:

4. **Under what conditions does a population reach consensus, polarization, or fragmentation?** We will review computational opinion dynamics models—including bounded-confidence frameworks and adaptive network theories—that describe how network structure can amplify confirmation bias, filter information diversity, and lead to ideological extremization, providing critical insights into the mechanisms driving today's polarized discourse.

Developing strategies to mitigate information disorder

The complexity of the modern information ecosystem is intrinsically linked to the rise of information disorder, which encompasses misinformation, disinformation, and mal-information. The widespread dissemination of false narratives, often amplified by coordinated campaigns involving automated accounts, represents a major societal risk.

The final aim of this review is focused on practical applications:

5. **Can we design effective, physics-informed interventions to mitigate misinformation diffusion?** By fully understanding the dynamics—including the roles of simple vs. complex contagion, threshold effects, and temporal properties like burstiness and non-Markovianity—we can lay the groundwork for developing counter-strategies capable of disrupting malicious cascades and fostering a healthier informational environment.

Limitations. As most of the results presented draw on evidence from online social platforms, it is worth recalling a major limitation recently highlighted in the literature to properly contextualize these findings [61,62]. Most research focuses on a narrow group of high-income democracies, with the United States dominating the field. However, the organization of political communication is correlated with the electoral system, which influences the extent of cooperation among political actors [63,64]. In this respect, the U.S. plurality system represents a specific institutional setting that tends to foster polarization. On the other hand, countries with proportional electoral systems tend to show lower levels of polarization and more frequent interactions across opposing political camps [63,64]. As a consequence, generalizing findings from one country to others is risky, as different political environments can substantially affect the outcomes of studies and limit their applicability.

1.2. Positioning with respect to existing reviews

The topics covered in this review lie at the intersection of several well-established strands of literature, ranging from statistical-physics approaches to social dynamics to computational studies of information diffusion, misinformation, and online polarization. It is therefore important to clarify both the points of contact and the specific contribution of the present article relative to previous reviews.

A first natural reference is the broad literature on sociophysics and statistical physics applied to collective social phenomena. Classical reviews such as [19,65,66] have played a foundational role in establishing the relevance of physical concepts and tools for the study of social systems. In particular, [19] offered a landmark synthesis of opinion, cultural, and social spreading dynamics, while [65] reviewed a specific but influential family of Galam-type models, and [66] surveyed opinion dynamics from a broader multidisciplinary perspective. These works remain essential references for the field. However, they were written before the current socio-technical ecosystem fully emerged in its present form, namely, a digital environment shaped by large online platforms, algorithmic curation, automated accounts, large-scale trace data, and the central societal role of misinformation and platform-mediated political communication.

A second line of related literature is formed by reviews specifically devoted to opinion dynamics. In this respect, the recent review by Starnini et al. [67] provides a timely and much-needed synthesis of the field from the perspective of statistical physics, with particular emphasis on conceptual foundations, empirical work, individual-based models, and current frontiers. Likewise, the survey by Shirzadi et al. [68] offers a broad and systematic overview of opinion-dynamics models within a unifying framework, with particular attention to convergence properties, algorithmic questions, viral marketing, and the role of node-level characteristics. These two reviews are clearly close to part of our scope, especially in relation to the modeling of consensus, polarization, fragmentation, and the dialog between empirical observations and theory. However, our review is not centered on opinion dynamics alone. Rather, opinion formation is treated here as one component of a wider problem involving the circulation of news and rumors, the empirical structure of the contemporary media ecosystem, the specific dynamics of misinformation, and the interplay between spreading processes and endogenous opinion change on socio-technical networks.

A third relevant stream is constituted by surveys on information diffusion in online social networks. The review by Guille et al. [69] has become a standard reference in this area by organizing early work on diffusion processes, cascade analysis, and diffusion models in online social platforms. Similarly, the survey by Li et al. [70] systematized the literature on diffusion models and methods, offering a useful classification of the main methodological approaches. More recently, Singh et al. [71] reviewed information diffusion analysis from the perspective of process, modeling, deployment, and

applications, thereby providing a broader synthesis that also includes tasks such as influence maximization, community detection, and link prediction. These reviews substantially overlap with our discussion of spreading models and empirical diffusion patterns. Nevertheless, their main focus is the diffusion process itself, often in a general data-mining, machine-learning, or computational-social-science setting. By contrast, our goal is to place information diffusion within a broader statistical-physics framework that explicitly connects network structure, out-of-equilibrium dynamics, rumor and news propagation, misinformation cascades, and the emergence of collective states such as polarization and echo chambers.

Another adjacent body of literature concerns misinformation and related forms of information disorder. For example, the survey by Zhou and Zafarani [72] offers a widely used overview of fake-news research, with particular emphasis on theoretical foundations and detection methods. This is highly relevant to our discussion of misinformation, especially insofar as false content cannot be studied only through its semantic features, but also through its propagation patterns and source characteristics. At the same time, the primary focus of that survey is detection, whereas our emphasis is on the collective dynamics of dissemination, reinforcement, and interaction with opinion formation. In this sense, misinformation is not treated here merely as a classification problem, but as a dynamical phenomenon unfolding on adaptive and heterogeneous socio-technical systems.

The present review is also related to the broad literature on network science and null models. In particular, [24] provides a comprehensive account of the statistical-physics approach to real-world networks, including maximum-entropy methods and null models. This perspective is directly relevant to our approach, because several empirical regularities discussed in the context of online social systems only become meaningful when contrasted against appropriate null hypotheses. Yet our objective is not to review network theory per se. Instead, network methods are presented here as part of an integrated toolkit for understanding the coupled dynamics of structure, information flow, and opinion evolution in digital communication environments.

Finally, some more specialized reviews address phenomena that are important for our scope but not sufficient, taken individually, to capture it entirely. Reviews on echo chambers and polarization, such as [73] and more recent systematic syntheses of echo-chamber research, are highly relevant for parts of our discussion, especially where we address homophily, fragmentation, and ideological reinforcement. However, these works typically focus on a specific mesoscopic phenomenon, whereas our aim is to embed such outcomes into a larger account that also includes platform structure, spreading mechanisms, rumors, misinformation, and the statistical-physics models used to describe them.

These observations help clarify the perspective of the present article. Our goal is not simply to provide another review of opinion dynamics, nor another survey of information diffusion, nor a review limited to fake news or echo chambers. Rather, we aim to bridge these traditionally separated strands of literature. More specifically, the added value of this review lies in four main aspects. First, it brings together *news*, *rumors*, and *opinions*, which are often studied in partially disconnected communities despite being tightly intertwined in real online environments. Second, it combines *empirical findings* and *physics-based modeling* within the same narrative, emphasizing both what large-scale data reveal and which theoretical tools are needed to interpret such evidence. Third, it explicitly grounds the discussion in the contemporary *media ecosystem*, including platform differences, information disorders, and the role of coordinated or automated activity. Fourth, it frames these issues within a coherent *statistical-physics and network-science perspective*, showing how concepts such as contagion, criticality, stochasticity, null models, and coevolution can be used to organize and interpret a broad and heterogeneous literature.

For these reasons, we see the present review as complementary to the existing ones. Rather than replacing them, it aims to connect them: the statistical-physics tradition on social dynamics, the literature on information diffusion, the work on misinformation, and the rapidly expanding scholarship on opinion polarization and echo chambers. We believe that this integrative perspective is especially useful today, because the same socio-technical systems simultaneously host information cascades, manipulative content, attention competition, community segregation, and endogenous opinion change. Understanding these phenomena in isolation is often insufficient; the main ambition of this review is precisely to highlight their common mechanisms and their mutual interdependence.

The role of statistical-mechanics ideas in this review. To help orient the reader throughout the manuscript, we emphasize that statistical-mechanics ideas enter in different ways and with different degrees of empirical grounding (see Table 1). In some parts of the review, the connection is direct and methodological, most notably in ensemble-based reasoning, maximum-entropy constructions and null models used to distinguish informative structure from constrained randomness. In other parts, statistical-physics models provide coarse-grained descriptions of threshold phenomena, contagion, and collective alignment, and are therefore useful for identifying minimal mechanisms behind recurrent empirical regularities. Finally, in a more limited set of cases, concepts such as criticality, scaling and universality are discussed as interpretive hypotheses or organizing principles whose empirical support in online information diffusion remains suggestive but still context dependent. For this reason, the role of statistical mechanics in the present review is not uniform across sections: in some cases it provides a direct benchmark framework, in others a parsimonious modeling language, and in others a broader interpretive perspective.

1.3. Organization

The remainder of this review proceeds as follows. We begin by establishing the necessary theoretical framework. Section 2 introduces the essential models of complex networks, covering structural properties of real-world socio-technical graphs and the probabilistic, mechanistic, and null models used for their analysis. This is followed by Section 3,

Table 1

Hierarchy of the different statistical-mechanics lenses used in the present review.

Typical concepts	Role in the review	Function in the review	Empirical status in online social systems
Maximum-entropy ensembles, Gibbs-like graph models, null models, constrained randomness	Direct methodological framework	Define benchmark expectations, assess significance, and separate structural effects from informative deviations	Strongest and most direct
Branching and percolation thresholds, epidemic-like models, mean-field approximations, spin and synchronization-inspired models	Coarse-grained dynamical modeling	Identify minimal mechanisms behind cascades, persistence, alignment, polarization, and fragmentation	Mechanistically illuminating, but assumption-dependent
Criticality, scaling relations, universality, phase-like transitions	Interpretive or organizing framework	Organize heterogeneous findings and motivate cross-system comparison	Suggestive, but sensitive to observables and coarse-graining
Platform affordances, algorithmic mediation, partial observability, hidden interactions	Boundary conditions for empirical applicability	Delimit the empirical conditions under which theoretical abstractions can be meaningfully interpreted, tested and validated	Essential for interpretation, but limited evidence for statistical-mechanics claims

which reviews the core physical models of social dynamics, including classical frameworks like percolation, epidemic-like compartmental models, and spin models, which form the basis for understanding collective behavior.

We then ground these concepts in the modern context. Section 4 details the main elements forming the present-day media ecosystem, offering a comparative discussion of major platforms (e.g., X, Facebook, Reddit) and summarizing the novel information disorders that have emerged in this context.

The core of the review applies this toolkit to specific collective phenomena. Section 5 focuses on information spreading. This section first details the models of dynamics (from simple to complex contagion, including cognitive factors) and then presents empirical insights on topological and temporal characteristics. Crucially, it includes an in-depth analysis of misinformation dynamics, models, and proposed mitigation strategies. Following this, Section 6 addresses models of opinion dynamics. We review major modeling paradigms, including discrete opinion models (like the Voter model) and continuous models (like Deffuant–Weisbuch), concluding with the critical challenge of modeling the coevolution of opinions and social structure.

Finally, Section 7 offers a summary and draws conclusions, highlighting key findings and future research directions in this rapidly evolving field.

2. Models of complex networks

Modeling complex social systems as complex networks is crucial for understanding the intricate relationships and emergent behaviors that characterize human interactions. Traditional approaches often simplify these systems, overlooking the non-linear effects of connectivity. By representing individuals or entities as nodes and their interactions as links, network models allow us to capture the underlying structure of social connections, which profoundly influences phenomena like opinion formation, disease spread, and collective action. This network perspective provides a powerful framework to analyze how local interactions scale up to global patterns, revealing insights into the resilience, efficiency, and dynamics of social structures that would otherwise remain hidden.

2.1. Properties of real-world networks

Over the past two decades, the study of real-world networks—social, technological, biological, and information-based—has revealed a set of recurring structural features. These empirical properties are crucial for understanding processes such as diffusion, contagion, and percolation, and they serve as benchmarks for generative models of networks.

In the context of online socio-technical systems, these properties are not merely generic descriptors of networked data, but measurable structural regularities of the substrates on which news, rumors, and opinions spread. Their empirical relevance depends on how interactions are operationalized—e.g., follower, retweet, reply, mention, friendship, or hyperlink networks—and on the temporal and platform-specific window over which the network is reconstructed.

One of the most studied properties of real-world networks is the distribution of degrees across nodes. Many networks exhibit highly skewed degree distributions, where most nodes have only a few connections while a small number of nodes act as hubs with very high degree. Early studies suggested that such distributions often follow a power-law form, $P(k) \sim k^{-\alpha}$ with $2 < \alpha < 3$ [38]. This led to the characterization of many networks as “scale-free”.

However, subsequent large-scale statistical evaluations found that pure power laws are less common than initially believed. Instead, many networks are better described by truncated power laws, log-normal distributions, or exponential cutoffs [74,75]. Deviations from the idealized scale-free pattern, especially in the low-degree regime, have significant

implications for dynamical processes such as information diffusion or epidemic spread. For example, while hubs can dramatically lower epidemic thresholds, the scarcity of low-degree nodes may reduce the potential for long-tail spreading cascades.

Another hallmark of real networks is the “small-world” property: average path lengths are short, typically scaling logarithmically with the number of nodes [37]. This ensures that information or contagion can propagate efficiently across large systems. At the same time, real-world networks exhibit unusually high clustering coefficients compared to random graphs, reflecting the strong tendency for two neighbors of a node to also be connected.

Clustering is often heterogeneous, with a clustering spectrum that varies by degree: high-degree nodes typically exhibit lower clustering, while low-degree nodes belong to more tightly knit communities [76]. Such patterns suggest hierarchical or modular organization.

A pervasive property of real-world networks is the presence of community or modular structure: nodes cluster into groups with dense internal connections and sparse external links [77]. Such mesoscopic organization underpins functional specialization in biological systems, topic groups in citation networks, and social circles in human interaction graphs.

Communities can overlap, evolve over time, and exist at multiple scales. Their presence strongly influences diffusion dynamics: spreading processes can be slowed by modular boundaries, but inter-community bridges often serve as critical conduits for global cascades.

Networks also differ in how nodes of similar degree connect. Social networks often show assortative mixing, where high-degree nodes preferentially connect to other high-degree nodes [30]. In contrast, technological and biological networks are frequently disassortative, with hubs tending to connect to low-degree nodes.

Degree correlations significantly impact diffusion processes: assortative networks can facilitate robust spreading within highly connected cores, while disassortative structures enable rapid reach across peripheral nodes. Generative models often incorporate assortativity through rewiring mechanisms or correlation-preserving constraints.

The properties outlined above—heavy-tailed degree distributions, small-world effects, clustering, community structure, and assortativity—constitute the empirical foundation for modern network science. They highlight the limitations of classical random graph models and motivate the development of richer generative frameworks, such as preferential attachment, small-world models, stochastic block models, and fitness-based approaches. Any comprehensive survey of diffusion models must first situate them against these structural features, since they directly shape the pathways and thresholds of information spread.

For the purposes of information diffusion, the main point is that these regularities do not affect dynamics in a secondary way: they determine whether spreading remains local or becomes system-wide, whether reinforcement is confined within communities or reaches distant groups, and whether influential nodes are identifiable by local popularity or by their position in the global structure. In this sense, empirical network analysis provides the structural constraints that any realistic diffusion model must confront.

2.2. Probabilistic network models

The study of complex networks has been profoundly shaped by a number of foundational modeling frameworks, each of which highlights different mechanisms by which connectivity patterns may arise. Among the most influential contributions are random graph theory [78–80], the Watts–Strogatz small-world model [37], models based on suitable definitions of fitness [2,81], exponential random graph models (ERGMs) [82,83], stochastic block modeling [84,85], and latent geometry approaches [86]. Together, these frameworks form a diverse toolkit that can be used to illuminate distinct empirical regularities observed in social, biological, and technological networks.

Random graph theory, as formalized by Erdős and Rényi [78], considers the ensemble of graphs in which edges between node pairs are placed independently with equal probability. This simple generative prescription has the striking consequence that the typical distance between two randomly chosen nodes grows only logarithmically with the number of nodes: in this narrow sense, Erdős–Rényi (ER) graphs already display the “small-world” property of short path lengths. However, ER graphs fail to reproduce at least two ubiquitous empirical signatures, making these graphs unsuitable as faithful models of real complex systems, such as social networks. On the one hand, the model yields networks with Poisson-like degree distributions, as opposed to the heavy-tailed distributions of real networks. On the other hand, in ER ensembles the clustering coefficient (the tendency of neighbors of a node to be connected to one another) vanishes as the system size increases, whereas empirical networks present high local clustering.

The configuration model extends the ER model proposing a fundamental random graph ensemble that generates networks with an arbitrary, user-specified degree sequence [30,87]. Each node is assigned a number of half-edges (stubs) according to the desired degree distribution, and edges are formed by randomly pairing stubs until none remain. This produces graphs that exactly preserve the degree sequence while remaining maximally random in all other respects.

A distinct but complementary class of models was proposed to address the more general problem of reproducing a set of desired network properties. Exponential random graph models (ERGMs) [82,83] extend the random graph paradigm by endowing the ensemble of networks with a Gibbs-like probability distribution that explicitly biases graph occurrence according to chosen structural features. Formally, ERGMs assign to each graph a probability proportional to $\exp(-\sum_i \theta_i C_i(G))$, where the $C_i(G)$ are structural statistics (e.g., total number of edges, degree counts, numbers of triangles) and the θ_i are parameters (Lagrange multipliers) that control their expected values in the ensemble. In this

way ERGMs provide a principled, maximum-entropy style route to generate networks that match empirical constraints while remaining otherwise as random as possible. Their flexibility makes ERGMs particularly attractive for social network analysis, because one can tune the model to reproduce effects such as degree heterogeneity, homophily, and triadic closure. At the same time, this flexibility comes at a cost: parameter estimation and sampling in ERGMs can be computationally demanding, prone to issues of model degeneracy and poor mixing, and often requires careful model specification and diagnostics for reliable inference.

The Watts–Strogatz (WS) model [37] addressed a complementary limitation of simple random constructions by proposing an extremely parsimonious mechanism that interpolates between regular order and randomness. The WS recipe begins with a regular ring lattice in which each node is connected to its k nearest neighbors, a structure that yields very high clustering but long average path lengths. A single parameter, the rewiring probability p , controls the transformation: with probability p each edge is detached from its original neighbor and reconnected to a uniformly chosen random node, avoiding duplicates and self-loops. Two extremes are notable: when $p = 0$ the network remains the original lattice (maximal clustering, large distances), while when $p = 1$ the network becomes essentially a random graph with short distances but negligible clustering. Crucially, for small but nonzero values of p the WS construction produces networks that simultaneously exhibit high clustering and short average path length: a few randomly rewired edges act as shortcuts across the lattice and drastically reduce global distances while the dense local neighborhood structure responsible for clustering is preserved. This two-effect behavior—shortcuts + retained local structure emerging by tuning a single parameter—was one of the first parsimonious explanations for how empirical networks can combine global navigability with strong local cohesion, and it highlighted the importance of wiring heterogeneity (shortcuts) in producing the small-world phenomenon in a clustered substrate.

A different modeling perspective focuses on intrinsic node heterogeneity rather than on topology-preserving rewiring. In fitness-based or hidden-variable models [2,81], each node is endowed with an intrinsic attractiveness or fitness drawn from a distribution; the probability that two nodes connect is then a function of their fitnesses. This mechanism can generate heavy-tailed degree distributions and reproduce degree heterogeneity observed in many empirical systems without invoking explicit growth dynamics. Extensions incorporate evolving fitnesses, multiple fitness dimensions controlling different types of ties, or coupling between fitness and spatial/semantic proximity; fitness models therefore provide an appealing route to explain degree variability as an outcome of latent, node-level attributes.

Despite the value of these paradigms, no single class of models captures all empirical regularities simultaneously. ER graphs capture short path lengths but lack clustering; WS graphs explain clustering and short paths but do not naturally produce broad degree heterogeneity; fitness models generate heavy-tailed degrees but do not by themselves explain modular structure or strong clustering at multiple scales. To bridge these gaps, subsequent modeling efforts have incorporated similarity or latent structure as an additional organizing principle. Latent space models [88] posit that nodes occupy positions in an abstract similarity space and that connection probabilities decay with distance; stochastic block models (SBMs) [84] encode group-based affinities and modularity explicitly, and degree-corrected variants [89] add node-specific parameters to account for heterogeneous degree while preserving community structure. Hierarchical and Bayesian extensions of SBMs [85,90] enable principled multiscale inference and model selection. From a complementary statistical-physics perspective, maximum-entropy ensembles [91] formalize null models constrained by empirical observables and have been generalized to incorporate correlated topologies, clustering constraints, and higher-order structures [92,93] (more details on this subject can be found in Section 2.4).

Finally, latent geometric formulations—most notably Random Hyperbolic Graphs (RHGs) and related constructions—provide a parsimonious unifying picture in which popularity (expected degree) and similarity are encoded as radial and angular coordinates in a negatively curved space. This geometric embedding yields heavy-tailed degree distributions, strong clustering, and navigable small-world topologies within a compact and interpretable generative mechanism [86,94–97], and has proven useful both as an explanatory model and as a practical tool for network synthesis and analysis. From a statistical-physics perspective, RHGs can also be formulated as maximum-entropy ensembles with constrained total system energy; this formulation naturally accommodates additional constraints, such as arbitrary mesoscale structures [98], although whether these extensions retain a genuinely geometric character remains unclear.

Let us conclude this section with a remark. Rather than viewing these models as interchangeable alternatives, it is useful to interpret them as responses to different empirical regularities: random graphs provide a baseline for sparse connectivity and path lengths; small-world models address the coexistence of local cohesion and global reach; fitness and hidden-variable models account for degree heterogeneity; and block or latent-space models capture mesoscale organization, similarity, and modularity. From this perspective, their usefulness for diffusion studies depends on which empirical feature one aims to preserve, explain, or treat as a null expectation.

2.3. Generative network models

A central strand in the development of network science has been the proposal of *generative models* in which the network grows or evolves through explicit rules that specify how new nodes and edges are added, rewired, or removed. Unlike purely statistical ensembles, these models are designed to capture the actual processes that drive the formation of links in real systems. In many cases, they were directly motivated by social networks, where ties emerge from concrete interaction mechanisms such as popularity, similarity, or repeated encounters. As such, mechanistic models can be seen as

stylized but insightful hypotheses about the micro-level dynamics underlying observed macroscopic structures [30,39]. In the present context, the interest of these models is not primarily in reconstructing network growth per se, but in identifying which microscopic mechanisms are plausible candidates for generating the structural features repeatedly observed in empirical online communication networks, such as heavy-tailed degree distributions, triadic closure, turnover of ties, and homophilic segregation.

The most influential example is the Barabási–Albert (BA) model [38], which introduced the principle of *preferential attachment*. In this framework, networks grow by the sequential addition of new nodes, each of which connects to existing nodes with a probability proportional to their degree. The resulting “rich-get-richer” mechanism naturally generates scale-free degree distributions, a hallmark of many real-world systems, including the Web and scientific citation networks. Although simple, the BA model provided a mechanistic explanation for heterogeneous connectivity patterns and inspired a large family of extensions: nonlinear preferential attachment rules, aging effects (where older nodes become less attractive over time), and fitness-based modifications where the propensity of a node to attract links depends on intrinsic qualities [2,99–101]. These refinements retain the core idea of cumulative advantage while incorporating more realistic assumptions about competition, obsolescence, or node heterogeneity.

Another class of mechanistic models was explicitly tailored to social networks. A well-known example is the *networked seceder model* by Grönlund and Holme [102]. Here the central mechanism is identity formation: individuals seek to distinguish themselves from the average while still remaining within a recognizable community. The algorithm operationalizes this by letting nodes compare their positions to others and rewire links towards neighbors of nodes that are farther from the population center. The emergent outcome is the spontaneous formation of community structure, a robust feature of empirical social networks that the BA model alone cannot capture.

Similarly, the Jin–Girvan–Newman model [103] was motivated by empirical observations of friendship networks among students. It combines three behavioral rules: (i) new friendships are more likely between individuals who already share mutual acquaintances (triadic closure), (ii) there is a cognitive or social cap on the number of friendships a person can maintain, and (iii) ties decay over time unless reinforced by repeated interaction. These simple but realistic assumptions lead to networks with clustering, turnover, and community-like structures, all of which are absent in purely degree-driven models. The explicit use of triadic closure in particular has been recognized as a key mechanism in shaping the topology of social networks, complementing the role of preferential attachment.

Further refinements include models that incorporate *homophily*, the tendency of individuals to form ties with others who are similar in attributes such as opinions, demographics, or geography. Homophily-driven attachment rules can produce modular networks and echo chambers, providing mechanistic insight into how social cleavages translate into network segregation [104]. Other models have focused on *temporal dynamics of link formation*, highlighting bursty and heterogeneous activity patterns: for instance, Myers and Leskovec [105] analyzed follower dynamics on Twitter and proposed mechanisms where exposure, novelty, and individual activity rates shape the formation and dissolution of ties. These mechanisms are especially relevant because they map naturally onto empirical observations from digital platforms: cumulative advantage is associated with visibility concentration, triadic closure with repeated interaction in local neighborhoods, and homophily with the persistent segregation of users by interest, ideology, or identity.

In summary, mechanistic models offer a complementary perspective to purely statistical or geometric ones. They provide explicit hypotheses about how microscopic processes—preferential attachment, triadic closure, identity formation, homophily, or activity bursts—combine to generate the large-scale structural features observed in empirical networks. While our review is not primarily focused on network formation, it is important to stress that the spreading of news, rumors, and opinions takes place on social substrates whose very structure is shaped by such mechanisms, often with strong feedback loops between information dynamics and network evolution. A key limitation, however, is that these mechanisms are rarely observed in isolation in real socio-technical systems. Empirical networks typically combine cumulative advantage, local closure, homophily, platform-mediated recommendation, and temporal turnover. For this reason, the main value of mechanistic models lies less in providing literal reconstructions of network formation than in isolating minimal processes that can be tested against specific structural signatures in data.

2.4. Testing the right model: null models & maximum-entropy ensembles

In Physics, it is standard practice to develop null models to separate genuine signals from random noise. These models partially encode the structure of the real system and are used to assess the statistical significance of empirical measurements. For example, null models were instrumental in the characterization of the Higgs boson's properties [106]. If a null model fails to reproduce an observed phenomenon—e.g., if the associated p -value falls below a pre-defined significance threshold—then the observation is considered informative, indicating that the model lacks key explanatory elements. Conversely, if the model reproduces the observation, the result can be attributed to the mechanisms already embedded in the model and is thus not considered to provide additional insight.

Selecting an appropriate null model is, to some extent, an art. Such models should reflect the essential characteristics of the empirical system while remaining sufficiently flexible, as overly restrictive models may obscure the distinct contributions of the various structural ingredients to the observed data. In the absence of specific model assumptions, a well-founded null hypothesis is given by the maximum-entropy random graph constrained by known empirical quantities. By construction, maximum-entropy null models are maximally random—based on the maximization of

Shannon information entropy—and thus serve as unbiased statistical benchmarks. Although rooted in Information Theory, maximum-entropy null models have a direct analogue in Statistical Physics through the canonical ensemble. In this context, the constraints used in entropy maximization play a role analogous to energy in the canonical ensemble. The formal equivalence between Statistical Physics and Information Theory was first established by Jaynes in 1957 [107]; a comprehensive application of this framework to complex networks is discussed in [24]. This approach has been successfully applied to systems such as international trade networks, financial networks [34], and, more recently, to Online Social Media.

The definition of maximum entropy null models is essentially structured in three steps, beginning with the empirical network to be analyzed, hereafter denoted as G^* .¹

First, one defines the ensemble $\mathcal{G}$, i.e., the set of all possible graphs with the same number of nodes, ranging from the empty graph to the fully connected graph [91]. Next, each graph in the ensemble is assigned a probability by performing a constrained maximization of the Shannon entropy over the ensemble, namely

$$S = - \sum_{G \in \mathcal{G}} P(G) \ln P(G).$$

If $\vec{C}(G)$ is a vector of quantities measured on a generic graph $G \in \mathcal{G}$ —for instance, the total number of links or the degree sequence—one may require the null model to be maximally random (i.e., to maximize its entropy) while fixing $\langle \vec{C} \rangle$, the ensemble-average of $\vec{C}$, to a prescribed value [91]. As in statistical ensembles, it follows that the probability satisfying these constraints has the form

$$P(G) = \frac{e^{-\vec{\theta} \cdot \vec{C}(G)}}{Z(\vec{\theta})}, \quad (1)$$

where $Z(\vec{\theta})$ is the partition function and $\vec{\theta}$ is the vector of Lagrange multipliers, analogous to the inverse temperature in the canonical ensemble.

Finally, to tailor the model to empirical data, one typically sets $\langle \vec{C} \rangle = \vec{C}(G^*)$, which determines the numerical values of the multipliers $\vec{\theta}$ [92,108,109]. Remarkably, for maximum entropy null models, this constrained entropy maximization is equivalent to likelihood maximization; other constructions may exhibit inconsistencies between their definitional constraints and the likelihood, thereby introducing nontrivial, hard-to-control biases in the analysis [109].

Let us conclude this paragraph with some remarks.

First, Erdős–Rényi random graphs, as well as Stochastic Block models, can be obtained through a maximum entropy approach, just constraining, respectively, the total number of links, and the number of links inside each block and between each couple of blocks [91,110]. Furthermore, the reader may have noticed the similarity between the probability per graph in Eq. (1) and the definition of Exponential Random Graph models. Indeed, Park and Newman first showed how ERGMs can be derived from a maximum entropy approach [91]. Nevertheless, there is a crucial difference in the way those models are used: in Section 2.2, models were presented to explain the network structures observed in empirical systems. In the present Subsection, the logic is reversed: instead of describing the phenomenon, the null model acts as a benchmark. By comparing the empirical system with a model that incorporates properties of the real system, one can identify non-trivial features of the empirical system that the constraints cannot explain. In principle, any model can serve as a null model; however, choosing maximum-entropy null models helps reduce the bias introduced in the statistical benchmark.

Second, in the canonical ensembles of Statistical Mechanics, the quantity determining each microstate's probability is global—namely, the total energy. In contrast, when applying the same framework to complex networks, the constraints are often local, defined at the node level. Consequently, the model incorporates more detailed information about the empirical data, akin to knowing the average energy of each particle in a gas. While in Statistical Mechanics the per-particle energy is less relevant since all particles have the same properties [111], in many online systems agent behavior follows fat-tailed distributions. For example, user activity metrics such as content creation, reposting frequency, and content virality often exhibit power-law-like behavior. Therefore, specifying the local “energy” at the node level becomes particularly informative [93,112].

Third, although one can in principle constrain any network-based quantity, in practice certain choices are preferred. In many cases, the degree and strength sequences are especially informative [112]. Moreover, linear constraints on the adjacency matrix—such as those enforcing degree or strength sequences—allow the factorization of each graph's probability into edge-specific probabilities [91]. Hence, these constraints are among the most popular.

Finally, a maximum entropy null model allocates weights and edges as randomly as possible, consistently with those constraints. In this sense, maximum entropy null models provide an ideal statistical benchmark for detecting an excess of connections among node groups, a feature of particular relevance for online social platforms, which often exhibit strongly modular structures [113,114]. Indeed, multiple studies have shown that users cluster according to shared interests, sensibilities, or political leanings. Accordingly, maximum entropy null models are especially effective for capturing such information.

For online social systems, this logic is especially valuable because many apparent regularities in information exposure, polarization, and community structure can arise either from trivial heterogeneity in user activity or from genuinely non-random organizing principles. Maximum-entropy benchmarks are therefore not only methodological tools, but a way of identifying which structural patterns are likely to matter for the diffusion of news, rumors, and opinions.

¹ All quantities marked with an asterisk * refer to empirical values.

3. Physical models of social dynamics

The study of complex social phenomena necessitates moving beyond static structural descriptions to embrace the dynamics that unfold upon these networks. While Section 2 provided the foundational graph-theoretical tools for characterizing the topology of socio-technical systems, this section introduces the physical models crucial for understanding time-dependent processes like spreading, influence, and collective behavior. Models rooted in statistical physics—originally developed to explain phase transitions, critical phenomena, and non-equilibrium dynamics in materials and biological systems—offer a powerful, parsimonious framework to capture the complex, active, and out-of-equilibrium nature of human interactions. Specifically, we survey approaches that model the propagation of states (e.g., adoption of information or infection), the spatial and temporal exploration of the network, and the collective alignment or polarization of opinions. These models allow for the quantitative investigation of how microscopic interaction rules translate into macroscopic societal outcomes.

The rationale for the present section is empirical as much as theoretical. Large-scale social data reveal a number of recurrent dynamical signatures—threshold-like onset of large cascades, heterogeneous outbreak sizes, bursty propagation, persistence versus extinction, and abrupt shifts between consensus, polarization, and fragmentation—that call for different classes of physical models. Rather than reviewing these frameworks as a self-contained catalog, we discuss them as minimal dynamical descriptions designed to capture specific aspects of observed social dynamics.

3.1. Percolation and branching processes

Percolation and branching processes are two fundamental stochastic frameworks that offer complementary perspectives on propagation phenomena. Their importance for socio-technical systems stems from the empirical observation that many spreading phenomena are characterized by sharp distinctions between local extinction and system-wide cascades, as well as by highly variable outbreak sizes. These are precisely the kinds of phenomena for which connectivity thresholds and reproductive fluctuations provide a natural first description.

Percolation theory considers the emergence of large-scale connectivity in a network when edges or nodes are randomly occupied with probability p [115,116]. At the percolation threshold p_c , the system undergoes a phase transition: below p_c , occupied sites form only small clusters, whereas above p_c , a giant connected component emerges that enables system-wide propagation. On random networks with arbitrary degree distributions, percolation can be analyzed using generating functions. If $P(k)$ is the degree distribution and

$$G_0(x) = \sum_{k=0}^{\infty} P(k)x^k, \quad G_1(x) = \frac{G'_0(x)}{G'_0(1)}, \quad (2)$$

then the condition for the emergence of a giant connected component is

$$G'_1(1) = \frac{\langle k^2 \rangle - \langle k \rangle}{\langle k \rangle} > \frac{1}{p}, \quad (3)$$

which yields the critical occupation probability p_c [117,118].

Branching processes, in contrast, model reproduction dynamics generation by generation. In the classical Galton–Watson process, each individual produces a random number of offspring according to distribution $\{p_k\}$, with generating function

$$f(s) = \sum_{k=0}^{\infty} p_k s^k. \quad (4)$$

The extinction probability q is the smallest nonnegative solution of

$$q = f(q). \quad (5)$$

If the mean number of offspring

$$m = f'(1) = \sum_{k=0}^{\infty} k p_k \quad (6)$$

satisfies $m \leq 1$, then $q = 1$ and extinction occurs almost surely; if $m > 1$, then $q < 1$ and there is a positive probability of survival [119–121]. In epidemiological and information-diffusion settings, m plays the role of a basic reproduction number R_0 : when $R_0 > 1$, widespread propagation becomes possible.

These two perspectives are deeply linked. On locally tree-like networks, the percolation threshold coincides with the branching-process criticality condition: above the threshold, the Galton–Watson approximation admits survival, and simultaneously the network exhibits a giant connected component [117,118].

Branching-process intuition also extends naturally to continuous-time settings via Hawkes processes. A Hawkes process has intensity

$$\lambda(t) = \mu + \sum_{t_i < t} g(t - t_i), \quad (7)$$

where μ is a baseline rate and $g(\cdot)$ is a triggering kernel. Each event can generate offspring events in time, and the average branching ratio is

$$n = \int_0^\infty g(s) ds, \quad (8)$$

which parallels the mean offspring number in Galton–Watson processes. If $n < 1$ the process is subcritical and event cascades die out quickly, while $n \geq 1$ implies potential unbounded growth [122,123].

In practice, percolation theory provides insight into global connectivity and final outbreak sizes, while branching processes capture early stochastic dynamics and extinction probabilities. Temporal models such as Hawkes processes enrich the picture by incorporating realistic timing of events. Modern studies of information diffusion increasingly integrate these perspectives, combining percolation for critical thresholds, branching-process approximations for early dynamics, and point-process models for empirical temporal patterns [123–125]. At the same time, these frameworks are most informative when the relevant process is dominated by transmission opportunities and stochastic reproduction. They are less suitable when adoption depends strongly on reinforcement, memory, or strategic behavior, which motivates the more elaborate social-contagion models discussed below.

3.2. Epidemic-like compartmental models

Network epidemiology models assume that network edges serve as the principal mechanisms of disease transmission. They generally abstract away many intricate biological facets to instead concentrate exclusively on population dynamics, focusing on how the disease spreads through the population as a whole rather than on detailed biological processes within an individual [126]. Each individual within a defined population is categorized into one of a limited number of possible, mutually exclusive states, often referred to as compartments. These models remain relevant for social systems because many empirical spreading processes—especially early-stage rumor diffusion, attention bursts, and repeated reshare dynamics—exhibit clear analogies with contagion, at least at a coarse-grained level. Their appeal lies in the possibility of summarizing complex dynamics through a small number of state variables and transition rates, which makes them analytically tractable and empirically calibratable.

There are three particularly notable compartmental models that are fundamental to understanding epidemic dynamics:

- In the $S \xrightarrow{\beta} I$ Model (Susceptible–Infected Model) the only permissible transition for an individual is from the “Susceptible” (S) compartment to the “Infected” (I) compartment. Once an individual becomes infected, they remain in the infected state indefinitely, meaning there is no recovery or removal from the infectious pool.
- The $S \xrightarrow{\beta} I \xrightarrow{\gamma} S$ Model (Susceptible–Infected–Susceptible Model) introduces a recovery mechanism, positing that infected individuals, after a certain period, eventually return to the susceptible state. This implies that they regain susceptibility and can be reinfected multiple times.
- Finally, in the $S \xrightarrow{\beta} I \xrightarrow{\gamma} R$ Model (Susceptible–Infected–Recovered Model) infected individuals eventually recover from the disease (or, in some contexts, die) and, crucially, gain permanent immunity, meaning they cannot be reinfected.

Of course, this analogy is imperfect: information does not spread in exactly the same way as pathogens, and recovery, forgetting, repeated exposure, or reactivation often have different meanings in social contexts. For this reason, compartmental models should be understood as baseline descriptions of state propagation rather than literal models of cognition or communication.

In the deterministic formulation of these epidemic models, the transition rules governing the movement of individuals between compartments are quantitatively expressed in terms of constant rates, with β generally used for the infection rate and γ for the recovery rate. Consequently, the macroscopic dynamic behavior of the epidemic, detailing how the numbers of individuals in each compartment change over time, is meticulously described by a system of coupled differential equations. These equations represent the average behavior of the population, assuming large numbers of individuals and well-mixed interactions.

The solution to the differential equations offers a valuable mean-field picture for large, perfectly well-mixed populations. In the SI model, all individuals eventually catch the disease, and the mean-field solution shows that the fraction of infected individuals increases sigmoidally, approaching 1 (the entire population) as time goes to infinity. The SIS and SIR models, instead, exhibit a crucial threshold behavior determined by the basic reproduction number, $R_0 = \beta/\gamma$. This dimensionless value quantifies the average number of secondary infections produced by a single infected individual when introduced into a completely susceptible population. When $R_0 \leq 1$, the epidemic will die out, because the recovery rate is high enough relative to the transmission rate to prevent a large-scale epidemic from sustaining itself. When $R_0 > 1$,

on the other hand, an epidemic occurs: in the SIS model, the disease will persist in the population, reaching a non-zero stationary state $i^* = 1 - 1/R_0$; in the SIR model, the disease will spread through a significant portion of the population (the epidemic size) before eventually dying out, primarily due to the depletion of susceptible individuals.

When transitioning from the simplifying assumption of fully-mixed deterministic models to the more realistic realm of stochastic models explicitly defined on networks, the underlying network structure becomes of paramount importance. The specific arrangement of contacts and relationships within the network significantly and fundamentally influences the epidemic's progression, its final extent, and its overall outcome. In particular, the homogeneous mean-field approximation works poorly for networks with a heterogeneous degree distribution.

To address this issue, Pastor–Satorras and Vespignani [127] proposed the heterogeneous mean-field (HMF) approximation, based on formulating a specific equation for the relative density $i_k(t)$ of infected nodes of degree k . Under the assumption that all links are equally likely—i.e., that the network follows the configuration model, see Section 2.2—the dynamical equation for the infected fraction $i_k(t)$ reads:

$$\frac{di_k}{dt} = -\gamma i_k + \beta k[1 - i_k - r_k] \Theta(t),$$

where $\Theta(t) = \sum_k \frac{k'P(k')}{\langle k \rangle} i_{k'}(t)$. Solving these self-consistency equations yields the epidemic threshold $\beta/\gamma > \langle k \rangle / \langle k^2 \rangle$.

The HMF has two main drawbacks: it neglects the actual structure and assumes that all nodes of degree k are equivalent, and it predicts a vanishing threshold for scale-free networks in the thermodynamic limit [128]. A further approximation, independently obtained by Wang, Chakrabarti et al. [129,130] and by Gómez et al. [131], is referred to as quenched mean-field (QMF) (as opposed to the HMF being annealed). The QMF is also called individual-based mean-field and it is based on studying the temporal evolution of the probability that a node is infected, considering the actual structure of the network. One approximates each node's infection probability $x_i(t)$ by

$$x_i(t) \approx -\gamma x_i + \beta \sum_j A_{ij}(1 - x_i)x_j,$$

treating neighbor states as independent. Linear stability analysis then shows an epidemic threshold at $\beta/\gamma > 1/\Lambda_{\max}$, where $\Lambda_{\max}$ is the largest eigenvalue of the adjacency matrix A of the network. This QMF result has been rigorously derived and verified for SIS dynamics [126]. Intuitively, the most connected core of the network sets the scale for spreading.

More general approximate methods that try to take various network structural considerations into account do exist [126,132,133], as well as more detailed epidemic models where, for instance, there can be intermediate states accounting for exposure periods where individuals are not yet infected [126,132,133]. More generally, for more complex epidemic models and arbitrary networks, the system evolution can be simulated, even on temporal [134] or higher-order [135] networks.

The main contribution of these approaches this review is to show how structural heterogeneity reshapes dynamical thresholds and persistence conditions. Their weakness is that they generally treat transmission as pairwise and memoryless, and are therefore less suited to contexts where adoption is driven by reinforcement, attention constraints, or social confirmation.

3.3. Diffusion, random walks, navigation and routing

The physics concept of diffusion has also been used as a model of social phenomena, albeit the term “diffusion” is often used in the social sciences for a different phenomenon, where whatever spreads does not need to have a conserved mass. These frameworks are useful not because information spreading is literally diffusive in all cases, but because they isolate different aspects of motion and accessibility on networks: unguided exploration, confinement in clustered structures, accelerated transport through shortcuts, and the possibility of reaching distant targets using only local information.

Physical diffusion [136] is the most basic dynamic process that allows information to flow between distinct parts of an online social network. In physics, the standard diffusion equation for a field $u(\vec{r}, t)$ can be written as

$$\frac{\partial u(\vec{r}, t)}{\partial t} = D \nabla^2 u(\vec{r}, t). \quad (9)$$

when the time derivative is equal to zero, the stationary solution corresponds to evaluating the Laplacian operator $\nabla^2 u(\vec{r}, t) = 0$. On a complex network with adjacency matrix $\mathbf{A}$, such as an online social system, we must consider a discretized field $\vec{u}(t)$, where $u_i(t)$ indicates the value of the field on node i at time t . Accordingly, passing to finite differences to describe the continuous derivatives of the field, the diffusion equation takes the form

$$\frac{\partial \vec{u}(t)}{\partial t} = (\mathbf{K} - \mathbf{A})\vec{u}(t) = \mathbf{L}\vec{u}(t), \quad (10)$$

which in the case of a stationary field $\vec{u}^*$ reduces to

$$\mathbf{L}\vec{u}^* = 0, \quad (11)$$

where $\mathbf{K}$ is the degree matrix—a diagonal matrix where $K_{ii} = k_i$ is the degree, or the number of neighbors, of the i th node—and $\mathbf{L}$ is the combinatorial Laplacian matrix.

Physical diffusion is the macroscopic counterpart of a random walk process. While it is a general powerful model to address the phenomenon, it is nonetheless a poor model of any kind of information propagation: (i) (Dis)information typically does not leave the spreader. (ii) The broadcast from a source node to its neighbors is not deterministic: either some neighbors might not be reached for some reason, or they are reached and do not want to spread further that piece of information, with or without modification. Accordingly, it is possible to consider other spreading processes that can capture various details observed in empirical systems. For instance, random walk dynamics might more accurately capture information diffusion if the information is spread from a node to a single neighbor due to some form of contact at time t . In this case, the governing equation is very similar to Eq. (11), where instead of the combinatorial Laplacian, the normalized Laplacian matrix defined by $\tilde{\mathbf{L}} = \mathbf{K}^{-1}\mathbf{L}$ appears.

Regardless of the specific spreading process considered, once the formalism is set up, estimating how long the information takes to reach a destination at a distance d from the source is possible. In physical diffusion, the mean square displacement, usually adopted for such a purpose, grows linearly with time. For active matter, and then presumably for temporal networks that rearrange their links, the presence of topological shortcuts, such as in small-world [37] and ultra-small-world networks [137], might lead to superdiffusion [138,139]. Nevertheless, specific other topological configurations, such as the ones characterized by strong topological clusters, where the similarity with echo chambers is evident, might trap the random walker into specific parts of a network for a long time, longer than expected from networks with less marked groups.

While diffusion and random walks offer valuable models for understanding how information spreads in an unguided, exploratory manner, the study of navigability and routing shifts the focus to how that spread can be deliberately optimized by following specific, efficient pathways. In social systems, this matters whenever one is interested not only in whether a signal can spread, but also in how efficiently it can traverse a heterogeneous network, which nodes or communities act as bottlenecks, and whether local information suffices to produce globally efficient paths. Refs. [140,141] highlight the significance of Stanley Milgram's famous “small-world” experiment, in which participants were asked to forward a package through their personal acquaintance networks [142,143]. This experiment served as a foundational case study and motivated a wide range of research in complex networks, notably through Ref. [37]. Beyond analyzing conditions for local clustering and the scaling of global path lengths, several studies emphasized that the experiment's main contribution lies in showing that individuals can effectively navigate social networks. This insight supported the broader view that humans are adept at managing their social ties [144,145]. Building on this idea, Ref. [140] proposed that people rely on a hierarchical mental representation of their social groups to perform such navigation.

The navigation problem becomes academically interesting when one has some partial information to guide the search for a path from the source to the target node [146,147]. In the limit of little information, in fact, the problem approaches random walks, whereas in the case of full information, it could be solved by standard shortest-path algorithms. The navigability of real-world complex networks can be significantly improved and explained by considering an underlying latent geometry, which allows for the efficient use of local information to guide the search for a path from a source to a target node [94,97].

A problem strictly related to navigability and information diffusion in complex systems is *routing*, that is, finding efficient message passing strategies to guarantee the delivery of some information piece to one or many target nodes in a network [148,149]. Key challenges include minimizing the number of hops, avoiding congestion, and ensuring reliable delivery with only local information available to each node.

Greedy Routing [150] is a localized routing strategy where, at each step, a message is forwarded to the neighbor that appears “closest” to the destination based on a predefined metric, such as geographic distance, a calculated shortest-path estimate, or some abstract “distance” in a latent space. The rule is simple: if node u wants to send a message to node t , it passes the message to its neighbor v such that $d(v, t) < d(u, t)$, where $d(\cdot, \cdot)$ is the distance metric, and v is chosen to minimize $d(v, t)$ among all neighbors. A significant limitation, however, is that greedy routing does not guarantee message delivery in all network topologies. Messages can become trapped in local minima where all neighbors are “further” from the destination than the current node, even if a global path exists.

Kleinberg's model, also known as the Decentralized Search Model [151,152], specifically addresses the “small-world problem” and how short paths can be found using only local information, a challenge that simple greedy routing often fails at. The model proposes a network construction where nodes possess both local links, connecting them to geometrically or socially close neighbors, and a few long-range links, connecting them to distant nodes. The key insight is that for efficient decentralized search, where greedy routing proves effective, these long-range links must be chosen with a specific probability distribution. Specifically, a node at position u creates a long-range link to node v with a probability $P(u \rightarrow v) \propto d(u, v)^{-r}$, where $d(u, v)$ represents the distance between them, and r is an exponent. Kleinberg demonstrated that if the exponent r is precisely equal to the dimensionality of the underlying space D (i.e., $r = D$), then a greedy routing strategy can locate the target in a poly-logarithmic number of steps, approximately $(\log N)^2$ for $D = 2$, where N denotes the network size. Conversely, if $r \neq D$, the search process becomes inefficient. This model thus offers a theoretical explanation for the navigability of social networks and the empirically observed “six degrees of separation” phenomenon, suggesting that efficient navigability arises from a precise balance in the formation of long-range ties.

To manage the inherent complexity of routing in very large networks, hierarchical routing strategies are employed. These strategies organize the network into a layered structure, thereby reducing the amount of information required at each node for making routing decisions [153,154]. Hierarchical structures achieve this by organizing the network's nodes

into logically defined clusters or hierarchies. Routing decisions are not made on a flat, global scale but rather at multiple levels of abstraction. These levels typically include global routing, which pertains to the process of routing messages between different clusters or higher-level hierarchical domains, where nodes at this level only need to know how to reach other clusters, not every individual node within them. Once a message has reached the appropriate high-level cluster, local routing mechanisms take over to guide the message within that specific cluster, and potentially its sub-clusters, until it arrives at the destination node.

For hierarchical routing, the total cost of routing a message is the sum of the costs incurred at each level of the hierarchy. This can be expressed as $C = \sum_{l=1}^L C_l$, where L represents the total number of hierarchical levels in the network structure, and C_l denotes the cost of routing a message at a specific level l within the hierarchy. This cost can be quantified in various terms, such as the number of hops, time elapsed, or computational effort expended.

3.4. Linear thresholds, independent cascades and influence maximization

A central framework for modeling the diffusion of information, ideas, and opinions in social networks is the *Linear Threshold Model* (LTM). In this model, each node v has an associated threshold $\theta_v \in [0, 1]$ and is influenced by its neighbors through weighted edges w_{uv} such that $\sum_u w_{uv} \leq 1$ [125,155,156]. A node becomes active once the cumulative influence of its already active neighbors exceeds its threshold, i.e.,

$$\sum_{u \in A \cap N(v)} w_{uv} \geq \theta_v,$$

where A is the set of currently active nodes. Starting from an initial seed set S , the process unfolds in discrete steps until no more activations are possible. The influence function $f(S)$ is defined as the expected number of eventually active nodes when S is the initial seed set.

These models became central in the study of social diffusion because empirical adoption processes often depend not only on pairwise transmission, but also on cumulative exposure, local reinforcement, and the strategic choice of seed nodes. They therefore provide a natural bridge between social-contagion data, threshold behavior, and intervention-oriented questions such as how to trigger or suppress large cascades. The threshold model naturally captures the phenomenon of *information cascades*, where individuals sequentially adopt behaviors or beliefs based on observations of their neighbors' actions [157]. The relevance of the threshold perspective is empirical as well as conceptual: many observed cascades appear to require more than a single exposure, especially when adoption involves risk, credibility, or social validation. In this sense, threshold models capture a mechanism that is largely absent from simple epidemic descriptions. This connects to the broader literature on social learning, where agents update their beliefs through observation of others' decisions, potentially leading to efficient information aggregation but also to fragile mass behaviors and learning blockages [158,159].

A relevant question is how to choose the k nodes that maximize the influence function $f(S)$. This *influence maximization problem* is NP-complete under general thresholds [125]. A natural restriction that makes the problem analytically treatable is requiring f to have a diminishing-return behavior. A typical example are submodular functions, for which, given a pair of sets $A \subseteq B$ and any element v ,

$$f(A \cup \{v\}) - f(A) \geq f(B \cup \{v\}) - f(B).$$

The submodular model is obtained from the general threshold framework by requiring that each local function f_v is submodular.

An alternative but closely related approach is the *Independent Cascade Model* (ICM) and its variants [125]. In this model, every edge (u, v) is assigned an activation probability p_{uv} . When a node u becomes active at time t , it has a single chance to activate each inactive neighbor v at time $t + 1$, with probability p_{uv} . Each attempt is independent of the others and of the past history. More general cascade models allow the activation probability p_{uv} to depend on the set A of neighbors that have already tried (and failed) to activate v , i.e. $p_{uv}(A)$. The classical ICM corresponds to the special case $p_{uv}(A) = p_{uv}$, constant and independent of A .

The cascade framework has been extended to capture more sophisticated dynamics, including heterogeneous agent behaviors [124], temporal network effects [49], and competitive diffusion scenarios where multiple pieces of information or products compete for adoption [160]. Recent work has also explored how network structural properties and correlations affect cascade dynamics, revealing that traditional mean-field assumptions may fail in realistic social network topologies [161].

Influence maximization under the general cascade model is also NP-complete [125]. However, as in the threshold case, tractability can be restored by imposing a diminishing-return condition. This leads to the *Decreasing Cascade Model*, in which $p_{uv}(S) \geq p_{uv}(T)$ whenever $S \subseteq T$: the more failed attempts are made to activate v , the harder it becomes to influence it.

The computational challenges of influence maximization have spurred considerable algorithmic innovation. Beyond the seminal greedy approximation algorithm of Kempe et al. researchers have developed more scalable approaches including the Cost-Effective Lazy Forward (CELf) algorithm [162], sketch-based methods for large networks [163], and reverse

influence sampling techniques [164]. These advances have enabled practical applications to viral marketing, social media campaigns, and public health interventions in networks with millions of nodes [165,166].

Together, the LTM and ICM constitute the two canonical frameworks for diffusion processes in networks. Their submodular variants are particularly important because they enable efficient approximation algorithms for influence maximization, with provable performance guarantees [125]. The rich interplay between information cascades, social learning theory, and algorithmic approaches to influence maximization continues to drive advances in understanding how information, behaviors, and innovations spread through complex social systems [167,168]. At the same time, these models inherit important limitations from their simplifying assumptions: influence is often reduced to monotone activation, strategic behavior is largely absent, and empirical calibration of thresholds or transmission probabilities is non-trivial. Their strength lies in isolating reinforcement and seeding effects; their weakness is that real communication environments are usually more heterogeneous, adaptive, and semantically structured than the models assume.

3.5. Spin models, oscillators and synchronization

The Ising model was originally introduced in the 1920s by Wilhelm Lenz and Ernst Ising as a simple model of ferromagnetism [169]. In its most basic form, the model consists of binary variables (“spins”) $s_i = \pm 1$ located on the nodes of a lattice. Each spin interacts with its neighbors through pairwise couplings J , and may also experience the effect of an external field h . The energy of a configuration is given by

$$E = -J \sum_{(i,j)} s_i s_j - h \sum_i s_i, \quad (12)$$

where the first term encodes local alignment and the second represents global bias. Despite its simplicity, the Ising model captures the emergence of collective order (magnetization) and the existence of sharp transitions between ordered and disordered phases [170,171].

The central importance of the Ising model lies in its role as a paradigmatic example of *critical phenomena*. Near the critical temperature T_c , the system exhibits long-range correlations, power-law fluctuations, and scale invariance. These features are not specific to ferromagnets, but are shared by a wide variety of systems, from liquid–gas transitions to neural avalanches [172,173]. This observation gave rise to the concept of *universality*: very different microscopic systems can exhibit identical macroscopic critical behavior, characterized by the same set of critical exponents and scaling functions [174,175].

In the context of complex systems beyond physics, the Ising framework provides a minimal representation of collective dynamics driven by local interactions. Individuals in a society, for instance, may be represented as binary spins indicating whether they adopt or reject a piece of news. Neighbor-to-neighbor influence corresponds to the coupling J , while external drivers such as mass media can be modeled by a field h . Just as in magnets, such simple local rules can give rise to macroscopic consensus, polarization, or sudden phase transitions in collective opinion [19,176,177]. Recent work has extended Ising-like approaches to model the spread of information and memes in online social networks, highlighting how social reinforcement and external fields (media, platforms) can push systems close to criticality, amplifying small fluctuations into large-scale cascades [178,179]. For this reason, Ising-like models are best viewed as coarse-grained representations of binary alignment and external bias, useful for clarifying possible mechanisms of consensus and polarization, rather than as literal reconstructions of the cognitive processes underlying opinion change. In fact, the importance in the present context of the Ising model is less that social systems literally obey an equilibrium Hamiltonian, and more that it provides a minimal language for studying collective alignment, susceptibility to perturbations, and abrupt macroscopic changes emerging from local interactions. Then, while scale-free fluctuations, abrupt shifts, and long-range correlations are suggestive of critical-like behavior in some datasets, direct evidence for well-defined universality classes in real information or opinion dynamics remains limited and often depends on the choice of observables, coarse-graining procedure, and temporal window.

Synchronization is a ubiquitous phenomenon in coupled dynamic systems, where individual components adjust their rhythms or states to align with each other. In social systems, this can manifest as the alignment of opinions, behaviors, or even emotional states among individuals. The Kuramoto model [180] is a classic and widely used mathematical framework to describe the dynamics of synchronization. It models a collection of N coupled oscillators, each possessing a specific phase ϕ_i and a natural frequency ω_i . The interaction between any two oscillators i and j on the network is typically represented by a sinusoidal coupling term, which tends to pull their phases closer together. The evolution of the phase of each oscillator is given by the differential equation:

$$\frac{d\phi_i}{dt} = \omega_i + \frac{K}{N} \sum_{j=1}^N a_{ij} \sin(\phi_j - \phi_i)$$

Where K is a global coupling strength, determining the strength of interaction between oscillators, and a_{ij} are the elements of the adjacency matrix. Despite its simplicity, the model reveals rich collective dynamics, including the emergence of phase synchronization, where a macroscopic fraction of oscillators lock into a common rhythm.

The appeal of synchronization models in social systems lies in their ability to describe gradual alignment, partial locking, and coexistence of coordinated and incoherent groups. Their empirical interpretation, however, is typically more indirect than in physical oscillator systems, since the mapping between measured social variables and oscillator phases is not unique. A primary consideration for Kuramoto-like models for social dynamics is the underlying social network structure. The topology of the network, whether it be scale-free, small-world, or random, profoundly influences the synchronization process and, consequently, the patterns of diffusion and opinion formation. Researchers meticulously incorporate these intricate network structures into their models to reflect real-world social connections [181], and have utilized variations of the Kuramoto model to investigate how opinions polarize or converge within a society, particularly under different network structures, ranging from highly connected to more fragmented communities [182]. Within this paradigm, each individual in a social network is conceptualized as an oscillator, and their interest for a spreading topic is represented by the phase of this oscillator. The interactions between individuals, such as conversations, debates, or exposure to others' viewpoints, are then modeled as the coupling strength between these oscillators. Modifications include bounded-confidence couplings and high-dimensional opinion spaces on unit spheres, leading to stable consensus or bipolarized states.

4. Modern media ecosystem

Contemporary information diffusion unfolds across an intricate ecosystem of channels, including traditional broadcast media, their digital successors, and a diverse array of online social networks (OSNs). Each platform generates rich digital traces—followers lists, repost logs, hyperlinks, reaction metadata—providing raw material for constructing graph-based models. In this section, we systematically detail the workflow for extracting network representations from primary diffusion tools, examine why each platform has attracted scientific scrutiny, summarize key empirical patterns uncovered to date, and discuss practical considerations such as API limitations, data biases, and ethical constraints. We also briefly review emerging properties of these networks at all scales. Finally, we report on the main issues introduced by this novel information paradigm.

This section serves two related purposes. First, it provides the empirical context in which news, rumors, and opinions actually spread, emphasizing that diffusion is shaped by platform-specific interaction rules, visibility mechanisms, and data affordances. Second, it clarifies that the networked systems analyzed in the rest of the review are not directly observed objects, but reconstructions based on platform-dependent traces. For this reason, the same theoretical model may have very different empirical relevance depending on which interactions are observable, how networks are extracted, and what forms of user behavior are amplified or suppressed by the platform architecture.

4.1. X (Twitter)

X (formerly Twitter—a name still prevalent in scholarly literature) continues to serve as a paradigmatic case study for at least two principal reasons.

First, the platform's constraint on message length rendered it particularly well-suited for the rapid dissemination of news and political messaging. From its inception, Twitter soon became one of the preferred platforms by journalists and political figures, who demonstrated high levels of activity (see, for instance, a report about Italian journalism [183]). In this regard, although Twitter users have never been demographically representative of the general population due to the platform's relatively limited diffusion compared to other social media, it has nonetheless managed, in many national contexts, to more accurately reflect and shape public and political discourse. The present situation, following the platform's 2022 change of ownership, marks a significant departure from this earlier role. The removal of content moderation, the algorithmic promotion of particular types of content, and the overall increase in polarization have, in recent months, led to a worldwide outflow of users and diminished the platform's relevance to public debate [184].

Second, the availability of data for academic research has historically made Twitter an exceptionally valuable object of study. Over the years, it has arguably granted researchers greater access to data than any other social media platform. However, the change in ownership has substantially complicated this access, making it practically impossible to freely retrieve data using the official API for research projects [185]. One exception is the European Union. Under the Digital Services Act (DSA), social platforms are required to disclose how their systems work to regulators [186]. In practice, however, access to data on platform X is only granted to research projects that have been approved by the platform itself—and even then, access is limited to a short time window.

In practice, users author posts (or *tweets*) of up to 280 characters, which can be reshared (or *retweeted*), quoted, replied to, or liked. Given the nature of this social network, different graph structures can be outlined. While in almost every case, the vertices are given by the other users of the service, an edge (directed) can be defined either by a following relation (I am the follower of another account) or by retweeting somebody else text. To study diffusion, researchers especially focus on the following complementary networks:

- *Follower network*: a directed graph where each edge (u, v) indicates that user u follows user v . This almost-static backbone is typically fetched via the REST API or academic “full-archive” datasets.

- *Retweet network*: a directed, temporal graph built by parsing retweet events. Each retweet at time t of an original tweet m yields an edge from the retweeter to the original author, annotated with timestamp t . Remarkably, the information about how the retweeter met the content that later retweeted, i.e. if she saw the original post by following the author of the post or if she is following someone that reposted the original message, is not available, thus limiting the analysis.
- *Mention and reply networks*: directed graphs in which edges represent explicit references: if user u mentions v , an edge (u, v) is added; if u replies to v , a similar edge is created. These networks capture conversational pathways and can highlight tightly knit conversation clusters [187].

From the perspective of diffusion research, X has been especially important because it made it possible to disentangle several layers that are often confounded on other platforms: a relatively stable backbone of potential exposure (the follower graph), temporally resolved traces of realized propagation (retweets), and conversational interactions (mentions and replies). This combination made the platform unusually well suited for testing hypotheses on cascade growth, bursty attention, influencer roles, and the mismatch between structural centrality and actual diffusion.

X's layered networks of follows, retweets, and mentions enable disentangling potential versus realized influence. One of the first comprehensive studies of the entire "Twittersphere" [188] showed that the follower-following network topology is characterized by a heavy-tail follower distribution, a short effective diameter, and low reciprocity, which represents a deviation from known characteristics of human social networks. Another interesting observation is a certain level of homophily among reciprocated accounts. Network nodes were ranked using three procedures to identify potential accounts: by the number of followers, by PageRank, and by the total number of retweets. Findings suggested that ranking by number of followers and PageRank accounts for independent information concerning ranking by number of retweets. Early work showed that cascade sizes follow a power-law distribution with heavy tails: most tweets die quickly, but a few go viral, reaching millions within hours [188,189]. While the follower network dictates potential reach, the retweet network governs actual diffusion. Temporal analyses reveal diurnal cycles and burstiness, which can be modeled with self-exciting point-process approaches to retweet activity [190,191]; studies of collective attention on Twitter also show strong early peaks followed by heterogeneous decay patterns over time [54].

It is worth noting that the user experience on the platform has evolved over the years. Users are more or less exposed to certain topics according to their interest in them, as evaluated by suitable algorithms. While this individuates different systems across time, most of the result presented here focus on the diffusion across channels that users decided themselves to create or conversely delete. These topics-based structures have already showed a reasonable stability. In particular, a non-directed edge can be created amongst different accounts if they participate in a specific discussion. The power of network theory allows us to define a metric in the space of opinions; for example, when considering politics, we can obtain a "spectroscopy" of politics, as in the activity of the website <https://politoscope.org>.

Before the 2022 change of ownership, data access was enabled by the Twitter REST and Streaming APIs, though public endpoints enforce rate limits (e.g., 900 requests per 15 min), leading some researchers to rely on academic licenses for full-archive access. Sampling biases between the Streaming "gardenhose" and the Firehose have been quantified, revealing that partial feeds can underrepresent rare but impactful events [192]. Additionally, tweet deletion and account suspension can create missing data. As mentioned above, in the present day, public endpoints do not allow downloading data, and free access to data for researchers, when possible, is subject to the approval of the platform. Ethical considerations include user privacy, informed consent for research, and adherence to X's terms of service.

4.2. Facebook

Facebook's platform centers on bidirectional friendships, complemented by public pages and groups. Facebook's user base remains over 2.5 billion monthly active users. However, unlike X, much user content is private, raising unique access and ethical issues. If X historically offered a privileged setting for observing temporally resolved cascades in an open follower system, Facebook has been particularly important for the study of clustered exposure, repeated social reinforcement, and algorithmically curated diffusion within densely connected social neighborhoods. Key network representations include:

- *Friendship network*: an undirected graph in which edges connect mutual friends. This network can be sampled via consenting participants using the Graph API, but full-graph access is extremely limited and subject to platform policy changes and privacy regulations.
- *Sharing network*: a directed graph where an edge (u, v) indicates that user v reshared a post originally published by u . Historically, this could be extracted via CrowdTangle or approved API apps, but CrowdTangle was discontinued on August 14, 2024. Its direct replacement, the Meta Content Library and API [193], is available only to qualified academics or non-profit researchers via the virtual clean room of ICPSR (*Inter-university Consortium for Political and Social Research* [194,195]) and lacks retroactive historical access and many export functionalities.
- *Reaction/comment networks*: for public posts, graphs can be constructed from reactions or comments. The newer Content Library API now includes public comments and view counts, but extraction is restricted to in-clean-room analysis and lacks many of the interactive or bulk-export features present in CrowdTangle.

- *Group membership bipartite network*: users and groups form two disjoint node sets; an edge connects a user to each group they belong to. Projection yields co-membership graphs. Pre-2024, some group metadata was accessible via CrowdTangle, but since its shutdown, access to group-level membership is even more restrictive and not publicly documented by Meta.

The amount of information stored in Facebook's posts and preferences is known to be incredibly efficient in the profiling of the users [196–198]. Analysis of the complete Facebook friendship network [199] showed a broad, right-skewed degree distribution that falls off more rapidly than a power law, although hubs certainly exist. Facebook was almost a fully connected network, with short average path lengths and high clustering. The small-world effect was also confirmed by measuring the average vertex distance of 4.74 [200] on the giant component. Users and friends on Facebook were highly clustered, and their friendships possessed dense cores. Moreover, community structure emerged at the scale of friendships between and within countries. In this respect, the social structure of Facebook-friendship networks was investigated considering a hundred American institutions [201]. Different dominant contributions were discovered by carrying out complementary measures of assortativity and regression model coefficients on observed ties to evaluate homophily at a local level and community detection to capture modularity at the macroscopic level.

These empirical features help explain why Facebook has often been associated with complex contagion, where multiple independent exposures from different friends increase the probability of adoption, rather than simple broadcast-like spreading: dense local neighborhoods, repeated exposures, and group-based interaction make reinforcement effects both more likely and more measurable than on more open microblogging platforms [202]. Empirical analyses reveal that the sharing network is highly clustered, leading to echo chambers in which homogeneous viewpoints reinforce themselves [203]. Facebook's structural and algorithmic features create a uniquely fertile environment for the proliferation of disinformation. As the world's largest social network, its core functionalities—including an engagement-optimized News Feed algorithm, viral sharing mechanics, and community-oriented Groups—systematically amplify controversial and emotionally charged content [204].

Access to Facebook's (Meta's) public data requires app review, and limited public page, group, and event content is now accessible primarily via the Meta Content Library & API. The Graph API enforces strict permission checks through an onerous App Review process and business verification. Developers report high rejection rates and multiple attempts before gaining approval, even for basic permissions like page access or comments retrieval. Meanwhile, as mentioned earlier, CrowdTangle has been terminated (August 14, 2024), and its replacement is only available via ICPSR's clean-room environments under stringent access terms.

Ethical challenges include obtaining user consent when appropriate, protecting anonymity, minimizing profiling risks, and complying with data-protection frameworks such as the GDPR for European users [205,206]. Thus, most academic research now focuses on publicly available pages, groups, events or verified profiles via the Content Library, avoiding private personal data and recognizing the constraints imposed by Meta's governance structure.

4.3. Reddit

Although Reddit is highly relevant in the USA, its global reach remains concentrated, as US users comprise 45% of all daily active users worldwide [207]. With respect to the previously described online social platforms, where users can form relationship ties, such as friendships or followings, Reddit has a distinct structure. Following its own description, “Reddit is a vast network of communities that are created, run, and populated by you, the Reddit users”². An effect of the self-organization of thematic *subreddits* is the presence of internal policies of behavior and users' moderation of the debates. Users interact mostly with content created by others in the subreddit by upvoting, downvoting or replying to it. While much discourse is public, the platform does not expose follower-like social ties; instead, researchers derive networks from posting and commenting behaviors:

- *User-subreddit bipartite network*: captures which users post or comment in which communities. Projections onto users reveal shared-interest networks; projections onto subreddits map topical co-occurrence [208–210].
- *Comment-reply trees*: for each post, the comment thread forms a rooted tree with edges from commenters to the users they reply to. Tree depth, width, and branching factor provide natural structural measures of engagement and discussion growth [211].
- *Cross-post and hyperlink network*: edges represent posts linking to other Reddit content or external URLs, facilitating study of cross-community information flow.

Reddit is especially informative because it shifts the focus from diffusion over explicit social ties to diffusion mediated by topic-based communities, moderation regimes, and conversation trees. As a result, it offers a useful counterpoint to follower- or friendship-based platforms and helps disentangle the respective roles of social structure, visibility rules, and community norms in shaping information spread.

The platform's compartmentalized “subreddits” act as ideological enclaves, where community-specific norms dictate information credibility. Research shows that while some subreddits (e.g., r/science) enforce strict moderation, others

² <https://redditinc.com/policies/reddit-rules>

(e.g., conspiracy-themed communities) foster unchecked rumor proliferation through upvote-driven visibility. This creates a paradox: Reddit's decentralized moderation can both suppress and amplify fake news, depending on subreddit culture.

Reddit diffusion research highlights how community norms shape content spread: niche subreddits can incubate content that later propagates to mainstream communities. Analyses of Reddit discussions indicate that posts in politics, sports, and current-events communities tend to generate deeper and wider discussion trees [211], while controversy is associated with more negative and anger-laden conversational dynamics [212]; by contrast, broadly agreeable content may spread across communities with less sustained back-and-forth exchange [213]. Voting dynamics also interplay with structural position, as highly upvoted comments gain visibility and catalyze further engagement.

Although Reddit API and third-party archives once enabled historical reconstruction and large-scale research, changes since mid-2023 have severely limited both ability and ethical permissibility. Most contemporary researchers rely on limited real-time data, moderator-mediated access, or new curated datasets.

4.4. Other media

While X, Facebook and Reddit are the most widely studied media for information diffusion, many others have been considered in the scientific literature; in the following, we briefly review the most important. The point of this brief survey is not to provide an exhaustive platform taxonomy, but to show that different media instantiate qualitatively different observability conditions and interaction topologies: follower-based systems, repost networks, encrypted group communications, and inter-media hyperlink structures each expose different facets of information diffusion and therefore motivate different modeling abstractions.

Instagram. Instagram emphasizes visual content—photos and short videos—with captions and hashtags providing textual context. Public profiles can be scraped or accessed via the Business Account API under stringent rate limits. Network constructs include: a follower network analogous to X's, though data availability is more limited; a user-hashtag bipartite network, which may be projected onto users to detect topical communities and trend propagation [214]; a comment-based interaction network, extracted from post metadata and co-commenting patterns, capturing direct and repeated interactions among users [215]. Hashtag diffusion studies reveal that network position (e.g., central influencers vs. periphery users) significantly affects spread: influencers spark broad initial exposure, while community members sustain propagation. Content virality correlates with visual aesthetics metrics (e.g., color composition) and hashtag novelty [190,214]. Homophily in follower ties is stronger than on X, leading to denser community clusters and slower but more targeted diffusion [216]. However, API restrictions and lack of streaming endpoints hinder comprehensive temporal analysis. Data collection often relies on manual scraping scripts, which require constant maintenance against layout changes and carry risks of account bans.

Weibo. Weibo parallels Twitter's structure but emphasizes repost comments, multimedia, and verified user badges. As the leading Chinese microblogging service, Weibo offers follower, repost, comment, and like interactions. Public data can be scraped or accessed via limited APIs. The possible network representations essentially coincide with those used for X: follower networks, repost cascades [217], and comment and like networks. Empirical and modeling studies of rumor diffusion on Weibo show that reposting dynamics can generate super-spreading behavior and epidemic-like amplification [218], while targeted debunking interventions on Sina Weibo can improve rumor-refutation effectiveness and help curb further spread [219]. Cascades on Weibo often display chain-like propagation in grassroots networks and star-like diffusion around celebrity accounts. Government censorship and bot activity introduce noise and structural breaks in diffusion patterns. Scraping is impeded by frequent layout changes and anti-automation defenses; partnerships with Chinese institutions can ease access but raise geopolitical sensitivities.

WhatsApp/Telegram. WhatsApp and Telegram's end-to-end encryption precludes direct observation of message content or network ties. Researchers thus rely on indirect methods: group membership hypergraph, where participants in a group chat form a hyperedge; forwarding chains, reconstructing cascades from metadata (e.g., unique message IDs) to build trees similar to retweet cascades. Because content and network ties are not directly observable at platform level, WhatsApp diffusion is typically reconstructed indirectly from publicly accessible groups or donated user data, using message-sharing traces and co-sharing relations to infer who shared the same content and when [220,221]. Studies on WhatsApp show that misinformation can spread rapidly within politically oriented groups and across interconnected co-sharing communities, with diffusion patterns that differ substantially from those observed on more openly observable public platforms [220,221]. Data collection hinges on user recruitment and informed consent. Legal obligations (e.g., GDPR) demand strict anonymization and secure storage.

Traditional and online mass media. Traditional outlets—newspapers, television, radio—have migrated online, creating additional data sources:

- *Media hyperlink network:* nodes are media outlets, edges are hyperlinks between articles. Crawling sitemaps or RSS feeds enables construction of this directed graph, revealing inter-outlet influence patterns [222].
- *Article comment threads:* each thread forms a reply tree similar to Reddit, allowing sentiment and engagement analysis.

Table 2

Comparison of information diffusion platforms and their network extraction characteristics.

Platform	Public data	API access	Primary graphs	Temporal logs	Limitations
X/Twitter	Yes	Academic Research (EU-only)/Business API	Follow, Retweet, Mention	Yes	API caps, DSA scope; Privacy, ToS
Facebook	Part	Graph API/Content Library API via ICPSR	Friend, Share, React, Group	Yes	Restricted permissions; GDPR, Consent
Instagram	Part	Graph API/Content Library API via ICPSR	Follow, Hashtag, Comment	Partial	Restricted permissions; GDPR, Consent
Reddit	Yes	API/Pushshift	User–Subreddit, Comment	Yes	Archival gaps; Sensitive content
Weibo	Part	Limited API	Follow, Repost, Comment	Partial	Censorship, Scraping; Geopolitical ethics
WhatsApp	No	None (user-sourced)	Hypergraph groups	Yes	Recruitment bias; Privacy, Encryption
Media	Yes	RSS/Scrape	Hyperlink, Comment, Share	Yes	Paywall, HTML changes; Copyright

- *Cross-platform sharing traces*: by linking news articles to their corresponding social-media posts and reposts, researchers can study how stories are adapted and propagated across platforms such as Facebook, Instagram, TikTok, and Twitter [223,224].

Agenda-setting research uses time-series on topic mentions across outlets to detect core–periphery structures, where a small set of agencies leads narrative diffusion and others follow with lag times. Temporal cross-correlation of article publication times quantifies influence hierarchies [222]. Comment-sentiment networks highlight polarization and echo chamber formation. Data access is achieved via RSS, web scraping, and social APIs; challenges include rate-limited requests, paywalls, and copyright constraints.

4.5. Comparative discussion of social media features

Extracting network representations from online social networks' platforms requires aligning the research question with data affordances and practical constraints. Twitter, Reddit, and other public OSNs have long provided rich, timestamped, user-level data, making them valuable resources for cascade reconstruction and temporal network analysis. But recent access restrictions have made retrieving even basic information increasingly difficult. Facebook and Instagram offer deeper insights into clustered communities and visual contagion, but impose stricter API restrictions. Weibo's large user base grants cross-cultural perspectives, though scraping challenges and censorship affect data fidelity. Encrypted platforms like WhatsApp demand novel hypergraph techniques and participant-driven data collection. Traditional media complement these insights by tracing narrative origins and intermedia transfer. Across all platforms, researchers must navigate rate limits, sampling biases, legal frameworks, and ethical imperatives, making the choice of network model and extraction pipeline as crucial as the analytical methods applied to the resulting graphs.

Building network representations for information diffusion requires careful orchestration of extraction pipelines, platform-specific data artifacts, and analytical models. Table 2 summarizes key features across platforms.

In sum, each platform's unique data model shapes the feasible network abstractions and subsequent analysis. The interplay between data accessibility, graph complexity (monoplex vs. multiplex vs. hypergraph), and ethical/legal constraints dictates methodological choices. Robust diffusion studies thus depend as much on meticulous data engineering pipelines as on advanced theoretical frameworks.

Let us conclude this subsection with a remark. Three broad empirical differences appear especially consequential for diffusion research. First, platforms differ in the relation between observable ties and actual exposure: on some systems, such as X, potential reach and realized propagation can be partially separated, whereas on others, such as Facebook or WhatsApp, exposure is more strongly mediated by opaque ranking or private-group structures. Second, platforms differ in the balance between broadcast, reinforcement, and conversational dynamics: microblogging systems favor rapid reposting and bursty attention, while community-centered or friendship-based systems make repeated exposure and moderation effects more salient. Third, platforms differ in observability itself: some provide rich public traces, while others expose only partial or highly filtered signals. These differences are not peripheral methodological details; they shape which empirical regularities can be established robustly and which theoretical abstractions are justified. From this perspective, the modern media ecosystem should be viewed not as a single networked system but as a family of heterogeneous interacting substrates. A central challenge for statistical-physics-inspired approaches is therefore to identify which coarse-grained properties are platform-specific and which may support more general descriptions in terms of heterogeneity, modularity, reinforcement, or critical cascade behavior.

Table 3
A short list of the most used terms to refers to the various levels of disinformation that is possible to encounter when navigating social platforms.

Concept	Description
Affective Polarization	Dislike of the “other side” [226]
Astroturfing	The practice of masking the sponsors of a message or organization to make it appear as though it originates from grassroots participants [231]
Echo chambers	The result of selecting a set of friends and information that adhere to our system of beliefs, thereby forming polarized groups [232]
False Amplifiers	Methods, such as false news, disinformation, or networks of fake accounts aimed at manipulating public opinion [233]
False News	News articles that purport to be factual, but which contain intentional misstatements of fact [233,234]
Information operations and coordinated inauthentic behavior	Actions taken by organized actors (governments or non-state actors) to distort domestic or foreign political sentiment [233]
Social bot, Sybil account	Computer algorithm that automatically produces content and interacts with humans on social media [235]
Misinformation	The spread of inaccurate information without malicious intent [233]
Disinformation	Inaccurate or manipulated information/content that is spread intentionally [233]
Infodemics	Overflow of information of varying quality that surges across digital and physical environments during an acute public health event. It leads to confusion, risk-taking, and behaviors that can harm health and lead to erosion of trust in health authorities and public health responses [236,237]

4.6. Information disorders in social media

Information disorder is an umbrella term to cover the multifaceted aspects and undesirable effects of the interaction between individuals and information. Following the definitions in Ref. [225], the *information disorder* can manifest in 3 main forms: *mis-information*, i.e. when false information is shared without the intent of producing harm; *dis-information*, i.e. when false information is intentionally shared to produce harm; and *mal-information*, i.e. when “genuine information is shared to cause harm”. From the very definition, it is clear that those terms are broader than other broadly used terms that will recur in the present review, such as *fake news*, which according to Lazer et al. [226] is “.. *information that mimics news media content in form but not in organizational process or intent*.”. These distinctions are not merely terminological. They matter empirically because different forms of information disorder may exhibit different production mechanisms, target different audiences, and generate different diffusion signatures. A central difficulty in comparing studies is precisely that the measured prevalence and impact of harmful content depend strongly on how these categories are operationalized.

More generally, complex adaptive information ecosystems are susceptible to various forms of exploitation, ranging from the diffusion of harmful content to coordinated inauthentic behaviors that manipulate individual and collective attention. Table 3 summarizes the main problems related to information diffusion in complex socio-technical systems, highlighting the diversity of mechanisms and outcomes. Variations in definitions across studies can produce divergent interpretations: for example, Vosoughi et al. [227] found widespread penetration of misinformation, whereas Grinberg et al. [228] reported that only a small fraction of users interacted with misinformation sources. Subsequent work suggests that the primary differences between true and false news lie in their “infectiousness”, rather than in the underlying diffusion mechanisms [229]. A recent report has monitored the presence of mis- and dis-information in various online social platforms (Facebook, Instagram, LinkedIn, TikTok, X/Twitter, YouTube) in some European countries (France, Poland, Slovakia, Spain) [230]. Among multiple different measurements regarding the first half of 2025, TikTok resulted in the most exposed social platform to misinformation, with ~20% of posts targeting misinformation. On the opposite side of the spectrum lies LinkedIn, with nearly ~2% posts delivering false or misleading information. Furthermore, the authors noted that accounts consistently spreading low-credibility information receive more engagement than high-credibility accounts on every platform except LinkedIn. The gap is particularly pronounced on YouTube and Facebook, where low-credibility accounts generate nearly eight and seven times, respectively, the engagement per post per 1000 followers compared to high-credibility accounts.

Finally, notice that the empirical study of misinformation and related disorders cannot be separated from questions of measurement, platform architecture, and exposure. The same apparent discrepancy in prevalence may reflect not only different user behavior, but also different definitions, sampling strategies, and visibility mechanisms.

5. Information spreading

In modern times, social media platforms such as Twitter, Facebook, Weibo, and Telegram have fundamentally reshaped how information propagates through society. Large-scale cascades of news or misinformation can unfold in minutes, and understanding why certain content “goes viral” has become a critical scientific and societal challenge.

Long before the rise of online social media, social and behavioral sciences had already established that information diffusion is shaped by cognition, perception, and social interaction. Early schematic representations of these mechanisms, such as those shown in Fig. 1, already emphasized that diffusion may proceed through different social channels and forms of mediation. Foundational contributions identified several mechanisms that remain central today: mediated communication and opinion leadership [238,239], the role of weak ties and bridging links in connecting distant social

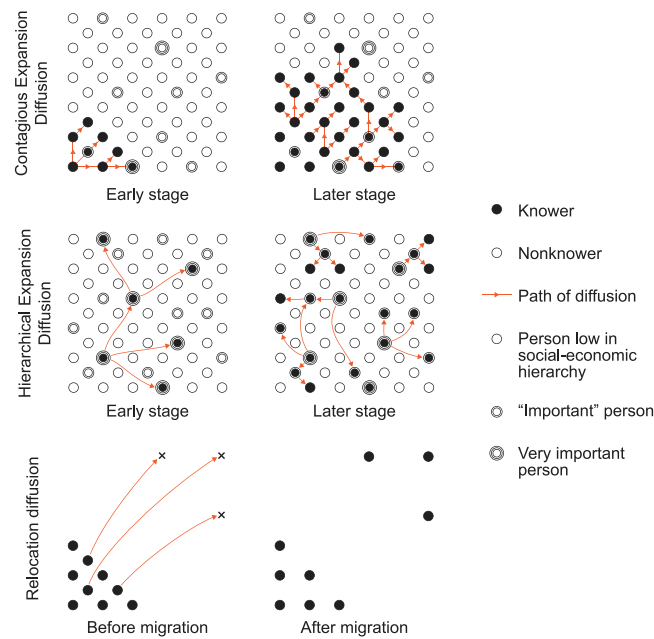


Fig. 1. Models of cultural diffusion—an illustration adapted from Jordan's 1982 *The Human Mosaic* [252]. (Slightly modified for consistency.) Note that “diffusion” in this figure is used in the sense of the social sciences and computer science: i.e., it does not preclude a change in the total mass of whatever spreads. Note also that the order of spreading is no longer thought to be determined by socioeconomic status [255].

groups [145], threshold-like adoption and social reinforcement [155,240], and selective exposure to attitude-consistent information [241]. Psychological research further showed that repeated exposure enhances persuasion [242,243], while cognitive biases and emotional salience affect both adoption and transmission [241,244].

This tradition also produced some of the earliest attempts to connect microscopic mechanisms to macroscopic diffusion patterns. Classical studies of innovation diffusion focused on the characteristic S-curve of adoption and on the distinction between innovators, early adopters, early majority, late majority, and laggards [240]. Related work considered how local interactions scale up to collective patterns, as in Hägerstrand's spatial diffusion models [245] and in early network approaches to diffusion [246,247]. These questions remain active in contemporary online settings, from innovation spreading across platforms [248,249] to the diffusion of linguistic novelties in social media [250,251].

These lines of work show that information spreading is not merely a transmission process on a network, but one mediated by attention, trust, social reinforcement, and the organization of social ties. They therefore provide the conceptual background for contemporary studies of online diffusion. The contribution of physics does not replace this perspective; rather, it adds a complementary layer of analysis by introducing coarse-grained dynamical models and rigorous benchmark tools that help quantify which empirical structures are genuinely informative, and which mechanisms are required to reproduce them.

Fig. 1 shows three different theories of the spreading of “ideas, innovations, and attitudes” from a 1982 cultural geography textbook [252]. In the eyes of a physicist “relocation diffusion” resembles convection in the theory of heat transfer, whereas “contagious expansion diffusion” is more like conduction. The other contagion model in Fig. 1, “hierarchical expansion diffusion”, is reminiscent of Lazarsfeld's two-step model of communication [238,239], originally intended to describe the influence of mass media on elections. It proposes a picture of simultaneous influence by mass media and network peers that has been confirmed in social media studies [253]. Its closest analogy among well-studied mathematical models (still too far to delve deeper into) might be reaction–diffusion systems [254].

A key point is that the study of information spreading is not driven by theory alone. The availability of large-scale digital traces—retweet cascades, sharing trees, temporal interaction logs, and cross-platform communication records—has made it possible to identify robust empirical regularities, such as heavy-tailed cascade sizes, strong heterogeneity in user activity, the importance of reinforcement, and the constraining role of community structure. In this context, theoretical models are most useful not as self-contained abstractions, but as tools to explain which microscopic ingredients are necessary to reproduce these regularities, and under which conditions they fail.

Conventional data-driven methods, network statistics approaches, or machine-learning classifiers often identify correlations without clarifying the structural or dynamical origins of the observed patterns. At the same time, social-science and behavioral frameworks have identified many of the relevant mechanisms, but they are not always formulated in a way that makes it straightforward to test how these mechanisms interact with large-scale network topology, temporal heterogeneity, or cross-platform coupling. In this context, statistical physics and complexity science contribute

in two complementary ways. First, they provide coarse-grained dynamical models—from epidemic-like and threshold-based processes to branching and percolation approaches—that can be translated to rumors, news, and other forms of information diffusion. Second, they provide rigorous methodological tools to assess the significance of the observed structures themselves. In particular, null models and maximum-entropy benchmarks make it possible to distinguish informative organization from constrained randomness, to clarify whether a structural pattern is more than a by-product of heterogeneous activity, and to identify which part of the empirical evidence a given hypothesis or mechanism is actually able to explain.

Models originally developed for ferromagnets, percolation in porous media, and epidemic outbreaks offer insights into how local interactions among users yield emergent, macroscopic patterns on social media. The problem of news propagation can be cast into a problem of spreading on very disordered and discretized media, where sites—e.g., newspapers, people, and mobile phone apps—form an interconnected web of communication channels. Furthermore, every site is not a simple but an active unit: it can start, terminate, or modify the process. Accordingly, such sites are more similar to active matter [256,257] characterized by non-linearity, lack of detailed balance and of time-reversal symmetry, and out-of-equilibrium dynamics.

By treating social media as a time-evolving network—nodes represent users and edges denote follower or friend relations—one can apply various physics-inspired models. These include epidemic-like compartmental models (SIR, SIS), percolation theory (site and bond), mean-field approximations, branching processes, and maximum-entropy ensembles. These methods are instrumental in capturing phenomena such as thresholds separating confined chatter from global virality, power-law cascade-size distributions near criticality, and the significant role of network topology in shaping diffusion dynamics.

This section builds on the structural foundation outlined in Section 2 to understand how information, such as news, rumors and memes, actually spread across network topologies. It explores various concepts, models, and techniques drawn from the field of physics and its applications, that offer a fundamental understanding of information diffusion in a broad sense. Our emphasis is not on reviewing models in isolation, but on assessing which empirical signatures—for instance threshold effects, bursty dynamics, structurally constrained cascades, or cross-platform amplification—motivate different modeling choices, and what these models actually explain about observed spreading phenomena.

To keep these different roles distinct, we organize the section around a small number of empirical objectives: identifying the microscopic mechanisms that govern adoption, clarifying how network structure and mesoscale organization constrain diffusion pathways, and assessing how temporal, multilayer, and higher-order effects reshape spreading outcomes. We then turn to the characterization and prediction of diffusion cascades, where cascades are treated as empirical objects in their own right, with attention to their aggregate regularities, scaling properties, and forecasting approaches. Finally, we discuss misinformation as a distinct domain in which several of the previous mechanisms combine with asymmetries in credibility, strategic amplification, and corrective interventions. Within each part, we relate the main empirical findings to the models and analytical tools proposed to account for them.

5.1. Spreading mechanisms

A first central empirical question concerns the microscopic conditions under which diffusion actually takes place. In some cases, a single successful exposure appears sufficient to trigger transmission, whereas in others adoption requires reinforcement, repeated encounters, or signals coming from distinct social contexts. This distinction is important because it determines which families of models can plausibly account for observed cascades.

5.1.1. From simple to complex contagion

The most fundamental type of social spreading process happens when something—an infection, an idea, the use of a product, etc.—spreads from one person to another. I.e., everyone who has the thing got it from exactly one other, but the total amount of what spreads is not necessarily conserved (as in random walks and physical diffusion discussed above). This type of spreading dynamics, where one spreading event is fully described by a unique transmission tree [258,259], is usually referred to as *simple contagion* [260]. Its simplicity, while allowing for a deeper mathematical analysis than other social processes [126,132,133], is sometimes seen as a limitation to their realism.

By far, most theoretical work on simple contagion has been done in the context of infectious disease modeling (cfr. Section 3.2), which in turn builds on results from percolation theory and branching processes (cfr. Section 3.1). Applications to information spreading illustrate the utility of these frameworks. In independent cascade or SIR-type models, each informed node transmits to neighbors with independent probability p , so the final set of informed individuals corresponds to a percolation cluster [117].

In Fig. 2 we see one information cascade from a 2002 e-mail chain letter [258]. While one might be tempted to model this type of information spreading as a simple contagion, the shape of this tree is very different from what one can naively expect from an SIR model, where, on average, infected people would be much closer to the infection source. This tree has 18,119 nodes, of which 17,079 (94%) have exactly one child. The median node depth is 288, and the width of the tree is 82. More generally, empirical studies of online adoption and cascade growth suggest that these simple mechanisms are often insufficient: in many settings, transmission depends not only on whether exposure occurred, but also on how many distinct exposures accumulated, from which social contexts they arrived, and how they interacted with limited attention and prior beliefs. This empirical evidence motivates moving beyond rumor-like and epidemic-like descriptions towards

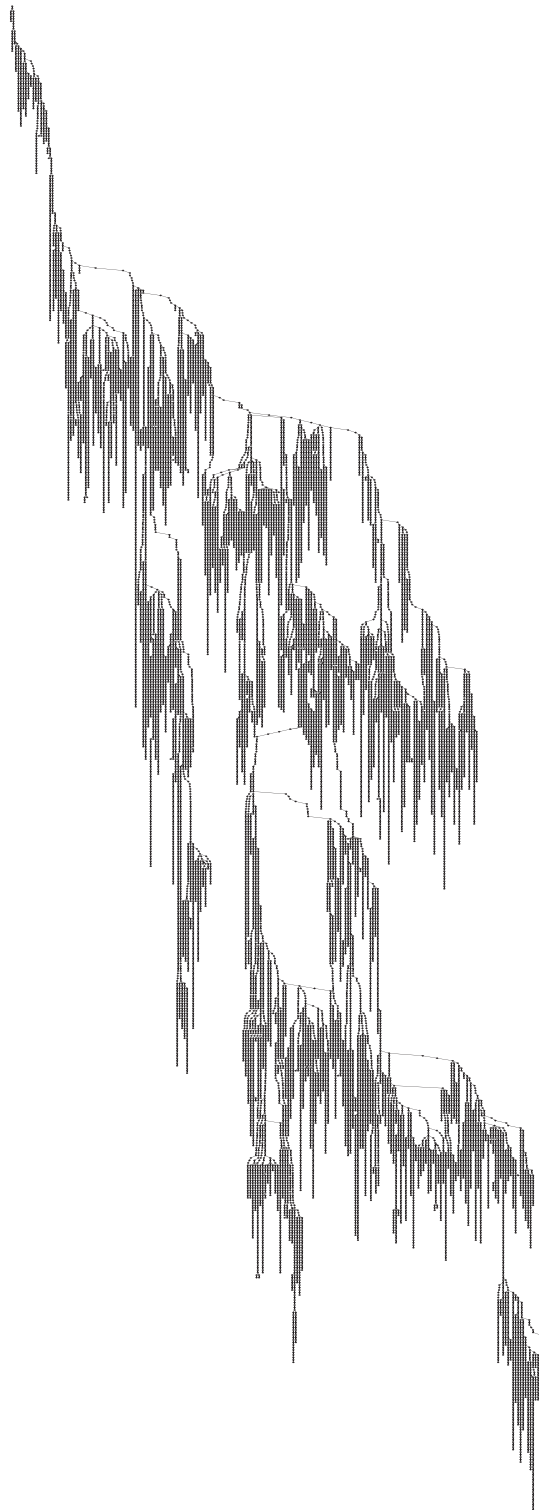


Fig. 2. A visualization from Ref. [258] showing the propagation of chain-letter e-mails petitioning against the 2002–2003 Iraq war. The generation number of the email increases downwards.

models in which adoption requires reinforcement, repeated exposure, or multiple converging signals, rather than a single successful contact.

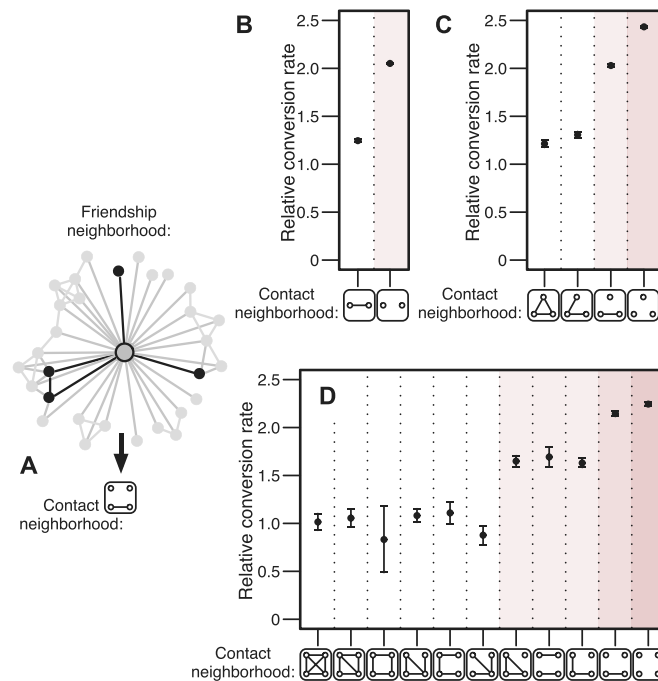


Fig. 3. A figure from Ref. [263] (studying the early growth of Facebook—the time when the platform primarily grew by email invitations) showing the paper's main finding. In (A), the black nodes are the focal node's friends who have sent the focal node an email invitation. This defines the “contact neighborhood” which the paper claims is the strongest determinant of the conversion rate (successful recruitment per time). Panels (B–D) show the relative conversion rates for two-node, three-node, and four-node contact neighborhood graphs. Shading indicates differences in component count. Invitation conversion rates are reported on a relative scale, where 1.0 signifies the conversion rate of one-node neighborhoods. Error bars represent 95% confidence intervals and implicitly reveal the relative frequency of the different topologies.

Empirical research has consistently highlighted the critical importance of reinforcement and threshold effects in adoption decisions. Multiple studies [261–263] demonstrate that diverse, multiple exposures significantly increase adoption likelihood compared to single or redundant contacts. Ugander et al. [263] showed that Facebook adoption during early expansion was best predicted not by the total number of invitations received, but by their structural diversity—specifically, the number of disconnected social clusters represented among inviters (see Fig. 3). Similarly, Aral et al. [264] identified reinforcement effects in a dataset of one million runners, while controlled experiments confirmed that adoption probability increases when influence comes from peers in distinct communities [202,265]. These findings reveal that social influence operates less like simple contagion and more as a cognitively mediated process where diverse contextual cues enhance salience and credibility.

Despite being often modeled with similar frameworks, in fact, epidemic dynamics and information-spreading dynamics exhibit fundamental differences in their underlying mechanisms and transmission patterns. A term often used to describe these extended contagion models is *complex contagion*. While some authors [264] use the term in a more specific sense, we will use it in a general sense, to refer to any mechanism where multiple exposures or reinforcing signals are required for transmission. This type of spreading is very common in social contagions, such as the adoption of new technologies, political movements, or risky behaviors, where social validation or perceived lower risk from multiple sources is necessary for adoption. Key mechanisms include:

- **Social reinforcement:** The probability of adoption increases with multiple exposures from different sources
- **Peer pressure:** Social influence that depends on the proportion of one's social circle that has adopted
- **Stifling:** The process by which individuals stop spreading information once they encounter others who are already aware of it
- **Threshold effects:** Where adoption requires a minimum number or proportion of activated neighbors
- **Memory and repeated exposure:** Where cumulative exposure over time influences adoption probability

5.1.2. Rumor models and reinforcement mechanisms

The pioneering Daley-Kendall [266,267] and the Maki-Thompson [268] models rely on the intuition that one key element that differentiates information from disease spreading is the decay of interest. They do so through “stifling” interactions: once a spreader has encountered enough people who are already aware of the news piece, they stop sharing it. In standard epidemic models, individuals who were previously infectious transition into the removed category through

death, isolation, or recovery, at a rate proportional to the number of infectious individuals. When it comes to news and rumors, however, individuals often stop spreading just because the information is no longer perceived as novel and potentially interesting. In both the Daley-Kendall and the Maki-Thompson models, a closed population is partitioned into three classes: ignorants (who have not heard the rumor), spreaders (who actively tell it) and stiflers (who know the rumor but no longer spread it). Spreaders contact others at random: when a spreader meets an ignorant the ignorant becomes a spreader; when a spreader contacts another spreader or a stifter the initiating spreader becomes a stifter (loses interest). These type of models have been widely used as baselines for analytical studies and network-based extensions of rumor/information propagation. For the sake of simplicity, they often assume that a single encounter with either another active spreader or a former spreader is sufficient to stop an individual from continuing to spread the rumor.

With the standard SIR notation—S being the ignorant, I the spreaders, R the stiflers—the probability for an individual to stop spreading information is proportional to the frequencies of meetings between members of the various classes. The list of the possible transitions in the time interval $(t, t + dt)$ with associated probabilities is the following:

$$(S, I, R) \rightarrow (S - 1, I + 1, R), \quad SIdt + o(dt); \quad (13)$$

$$(S, I, R) \rightarrow (S, I - 2, R + 2), \quad \frac{1}{2}I(I - 1)dt + o(dt); \quad (14)$$

$$(S, I, R) \rightarrow (S, I - 1, R + 1), \quad IRdt + o(dt). \quad (15)$$

The key aspect of this rumor-propagation mechanism is the lack of a threshold effect; the proportion of the population that eventually hears the rumor remains roughly constant, regardless of the population size, N . On complex networks, the presence of hubs alters outcomes: hubs quickly become stiflers and thus reduce the final informed fraction, though they accelerate early dissemination.

The Maki-Thompson framework has subsequently been extended in several directions, including networked versions, analytical refinements, and optimal-control formulations [269–273]. Ultimately, these studies show that rumor dynamics are shaped not only by transmission rates, but also by network heterogeneity and correlations, which can substantially alter both the speed of the process and the final informed fraction relative to homogeneous mean-field expectations.

The empirical evidence reviewed above suggests that in many online settings even rumor-like dynamics remain too weak a description, because adoption depends on cumulative and socially heterogeneous exposure. This is the point at which complex-contagion models become relevant. In an early model of complex contagion [155], Granovetter noticed that for some social spreading the cost of changing behavior (like joining a riot [274]) decreases with the number of social neighbors who already did. Then Granovetter stipulated that everyone has an individual threshold for changing behavior to arrive at his celebrated *threshold model* of collective behavior [155]. Threshold models are a common framework for describing complex contagion processes on networks. They formalize the idea that an individual's adoption of a behavior or idea depends on the number or proportion of their contacts who have already adopted it.

In the case of binary states, Watts' model [124] defines the following update rule for the state of a node i at time $t + 1$, denoted $x_i(t + 1)$ (where $x_i = 1$ if active/infected and $x_i = 0$ otherwise):

$$x_i(t + 1) = \begin{cases} 1, & \text{if } \sum_{j \in N(i)} a_{ij}x_j(t) \geq \phi_i \\ 0, & \text{otherwise} \end{cases}$$

Where $N(i)$ is the set of neighbors of node i , a_{ij} are the elements of the adjacency matrix, and ϕ_i is the individual threshold for node i . Possibly, only a subset of k neighbors sampled independently for each agent might be considered. In this framework, the condition for a cascade is that the largest cluster of most influenceable agents (with $\phi_i < 1/k$) percolates. If the underlying network is sufficiently sparse, cascade propagation is limited by the network's global connectivity; otherwise, if the network is sufficiently dense, it is limited by the stability of the nodes.

The model can be generalized to weighted networks, where the weight $w_{uv} \in [0, 1]$ represents the influence the u exerts on v [125]. Given a set S_0 of active nodes at time $t = 0$, the cascade develops deterministically in discrete time. At each time step t , each inactive node becomes active if the sum of weights on edges from activated neighbors reaches its threshold values. This linear model can be easily generalized by combining the influence of the neighbors by any monotone function f of the set of currently active nodes, such that $f(\emptyset) = 0$.

More generally, Watts's model triggered a gold rush of threshold-model studies, where physicists and other theoreticians modified it to: work on temporal networks [275,276], varying the influence of individuals [277], study the effects of bridge nodes [278], to account for the age of the phenomenon spreading [279], to allow for correlation between degree and threshold [280], or distance to the source and threshold [281]. Gleeson [282] proposed an analytically tractable model of cascades. Furthermore, complex contagion is often built into more intricate models of social phenomena, like the survival of minority opinions [283], the formation of youth subcultures [284], or climate action [285]. A general conclusion is that threshold models can reverse the insights from simple contagion models: in threshold models, bursty contact dynamics can speed up spreading [275,276], or depend little on long-range links [286], in contrast with epidemic spreading.

In an important contagion model interpolating between simple and complex contagion, Dodds and Watts [287] introduced the idea that individuals retain memory of past exposures to a contagious influence. At time t , each i receives

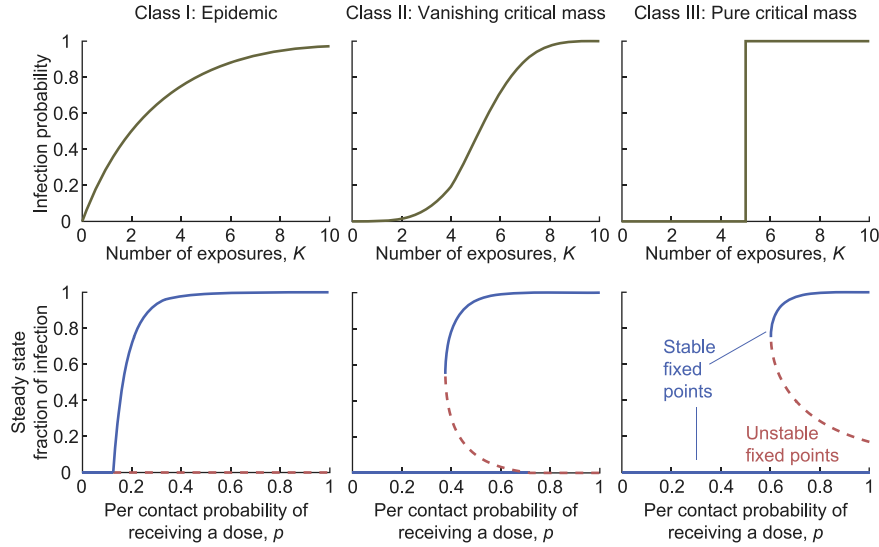


Fig. 4. The Dodds-Watts model of social contagion [287]. The top row shows the “dose–response curve”, i.e. the probability of an individual becoming infected given a number K of neighbors having been infected during the last unit of time. The second row of figures shows the steady-state fraction of infected individuals as a function of the probability of receiving a dose (contributing to the chance of contagion) from an infected neighbor.

a dose $d_i(t)$ from another randomly chosen individual j with probability p . The total amount of doses over the past T time steps

$$D_i(t) = \sum_{t'=t-T+1}^t d_i(t') \quad (16)$$

is kept stored: when $D_i(t)$ exceeds a given threshold d_i^* a susceptible individual becomes infected. A contagion model can belong to three universal classes depending on the equilibrium behavior. Class I includes the epidemic threshold models, which exhibit SIR-like dynamics with an epidemic threshold p_c corresponding to the level of infectiousness needed for an initial group of infected individuals to cause an epidemic. The other two classes require a critical mass to initiate and sustain the contagion. However, while in class II, the critical mass goes to zero for $p < 1$ (vanishing critical mass models), in class III, the critical mass remains always finite (pure critical mass models). Dodds and Watts’ study suggested that modifications to the individual’s threshold cause a considerable impact on the possibility of triggering a contagion and that the presence of easily influenced individuals increases the contagion’s chances more than the presence of highly influential individuals (a.k.a., opinion leaders). See Fig. 4 for an overview of the model’s behavior.

5.1.3. Behavioral heterogeneity and data-calibrated extensions

More recent work has tried to calibrate spreading mechanisms more directly on large social-media datasets, and formal models have been developed to capture social reinforcement mechanisms explicitly. Feng et al. [288] proposed a fractional-SIR (FSIR) model where susceptible users only become “infected” when the fraction of infected neighbors exceeds a threshold Γ , representing limited attention and information overload effects. When fitted to over one million Weibo cascades, the model identified empirical parameters $\beta_{\text{emp}} \approx 0.03$ and $\Gamma_{\text{emp}} \approx 0.2$ that successfully reproduced the observed truncated power-law distribution of cascade sizes.

Xie et al. [289] advanced this framework with a percolation-based model incorporating exposure-dependent adoption probabilities p_k that increase with the number of prior exposures. Analysis of large-scale Twitter and Weibo data confirmed this “social reinforcement” mechanism, showing that it effectively lowers percolation thresholds by 30%–50% compared to constant-probability models. Importantly, their work also revealed that automated bot clusters can exploit reinforcement dynamics to create spurious feedback loops that artificially amplify diffusion.

A closely related line of work emphasizes that diffusion is shaped not only by exposure structure, but also by heterogeneity in cognitive states, behavioral responses, and activity patterns. These ingredients help explain why users with similar network positions may nonetheless play very different roles in cascade growth, and why some epidemic-like models remain useful only after being enriched with psychologically meaningful state variables.

A central insight from the study of information diffusion is that spreading is not merely a structural process but is deeply shaped by human behavioral and cognitive mechanisms. The foundational work of Goffman and Newill [290] drew an influential parallel between infectious disease dynamics and the dissemination of ideas through the SIR model framework. In this analogy, individuals progress from being unaware or uninterested (susceptible, S) to adopting or

engaging with an idea (infected, I), and eventually losing interest or becoming resistant to further influence (removed, R). While initially metaphorical, this framework established the foundation for a rich class of models that explicitly incorporate behavioral states such as forgetting, attention decay, and psychological immunity, demonstrating how cognitive factors fundamentally shape cascade trajectories.

Building on this epidemiological perspective, researchers have revealed how psychological resistance and peer dynamics interact to determine diffusion outcomes. Ruan et al. [291] demonstrated through analytical and simulation studies that while even a small constant rate of spontaneous adopters suffices for global diffusion, the speed of equilibrium attainment is highly sensitive to the density of immune individuals. As immunity increases, diffusion transitions from rapid to slow propagation, reflecting the fundamental tension between peer-driven adoption cascades and psychological resistance to persuasion.

The predictive power of behaviorally-informed models has been validated in large-scale empirical studies. Castiello et al. [292] calibrated an Ignorant–Spreader–Recovered (ISR) model on over 40,000 Twitter cascades of COVID-19 hashtags, estimating infection and recovery rates (β , γ) via maximum likelihood. Their model achieved remarkable accuracy, predicting peak cascade volume with a mean absolute error of less than two hours, demonstrating that cognitive states such as attention and disinterest, when properly parameterized, enable both explanatory and predictive models of online behavior.

Individual heterogeneity in activity patterns represents another crucial cognitive-behavioral factor. Borge-Holthoefer et al. [293] adapted the SIS framework by incorporating node-specific activity rates λ_i that reflect differences in login frequency and engagement patterns. Empirical fits to Twitter subgraphs revealed that heavy-tailed distributions of λ_i —characterized by a few highly active users and many less active participants—substantially extend outbreak durations and fundamentally alter cascade-size distributions. This finding underscores that the heterogeneous rhythms of human activity are not merely technical details but defining features of collective dynamics.

In summary, simple contagion and rumor models remain indispensable baselines, both because they are analytically tractable and because they clarify which aspects of diffusion can already be explained by single-contact transmission and novelty decay. However, the empirical evidence on online adoption strongly indicates that many real cascades depend on reinforcement, threshold effects, activity heterogeneity, cognitive resistance, memory, and attention-related state changes. These are not secondary corrections to spreading models, but often determine their empirical realism. Models in this broader complex-contagion family are therefore needed whenever the observed diffusion patterns cannot be reduced to independent transmission events.

5.2. Network structure, heterogeneity, and mesoscale constraints on diffusion

A second broad empirical question concerns how network structure shapes diffusion outcomes. In online social systems, the probability that a cascade becomes large depends not only on who is initially exposed, but also on how connectivity is distributed across the network, how users are embedded in communities, and how strongly homophily and mediation structures constrain the available diffusion pathways. The literature shows that these effects cannot be reduced to local degree alone. Rather, spreading is shaped by a combination of degree heterogeneity, core–periphery organization, mesoscale embedding, and, in some cases, multilayer accessibility.

5.2.1. Centrality, core–periphery structure, and influential spreaders

Real-world directed networks exhibit hierarchical organization, often dominated by the emergence of leader nodes. Examples include dominance hierarchies in animal groups and food webs in ecology, master–slave couplings in control engineering, and source nodes driving contagion processes in social systems. At leading order, the presence of leaders can be inferred from the network degree distribution: within this simplified picture, leaders correspond to the most active nodes, i.e., those with the highest degree. Empirical analyses consistently report fat-tailed degree distributions, indicating that high-degree nodes constitute a vanishingly small fraction of the system, while the vast majority of nodes have low degree [188].

Nonetheless, a recurring empirical finding in online social systems is that influence is not determined solely by local connectivity, but rather by a node's position within the global and mesoscopic organization of the network [114,277,294]. In particular, nodes with high k -shell coreness systematically occupy structurally central positions for diffusion than nodes selected by degree, supporting a core–periphery interpretation of influence. Within this framework, the notion of “hidden influentials” naturally arises: nodes that are not hubs, yet occupy structurally central positions bridging otherwise distant regions of the network [295].

Evidence from political information diffusion on Twitter further indicates that influence is embedded in highly polarized interaction structures. Retweet-based similarity networks reveal pronounced echo chambers, i.e. sharply segregated, homogeneous communities, where users preferentially consume and propagate content consistent with their worldview [232]. In this setting, the out-degree of a node captures only a partial notion of influence, as information flows are strongly constrained by ideological segregation [296].

Segregation into weakly interacting communities can be quantified through entropy rates and measures of graph non-normality. It has been shown that, beyond a critical level of non-normality, entropy rates undergo an abrupt first-order transition to zero. This phenomenon has been linked to the emergence of leader nodes, defined as sink nodes with only

incoming edges [297]. The distance from such leaders induces a hierarchical ranking of the remaining nodes. Applying this framework to Twitter data during the COVID-19 pandemic revealed the presence of distinct knowledge communities, which shape global communication patterns [298].

Taken together, these results suggest that influence is a non-local and context-dependent property: hubs matter, but so do core–periphery organization, community boundaries, mediation structures, and the ability to bridge otherwise weakly connected regions. This empirical picture motivates models and optimization frameworks that go beyond degree-based heuristics.

Several modeling approaches have been proposed to formalize this idea. The Collective Influence (CI) metric introduced by Morone and Makse [299] and further analyzed in [300] explicitly incorporates multi-hop structural information through the quantity $(k_i - 1) \sum_{j \in \mathcal{B}(i, \ell)} (k_j - 1)$, thereby identifying nodes that act as connectors across distant regions. Empirical validation across multiple datasets shows that CI-based seeding strategies outperform degree-based heuristics, particularly in the low-budget regime, and that removing high-CI nodes rapidly disrupts global connectivity. These findings reinforce the interpretation of influence as a non-local, structurally mediated property.

From a different perspective, the identification of influential spreaders can be formulated as an optimization problem. Altarelli et al. [301] cast optimal seeding as the selection of a set of nodes maximizing the final outbreak size under SIR dynamics. Using belief propagation on a factor-graph representation, they derive a computationally tractable approximation that outperforms local heuristics.

These approaches are not only algorithmically useful: they also clarify which structural ingredients must be retained in coarse-grained descriptions of spreading. In particular, they show that the ability to trigger system-wide diffusion depends on paths and bottlenecks extending well beyond the immediate neighborhood of a seed.

Topological features capturing this heterogeneity can hinder global diffusion. Early studies show that hubs may transition prematurely to inactive states, thereby suppressing further spreading [302,303]. Similarly, the work of Zanette [304,305] demonstrates that structural randomness governs the transition between localized and global spreading regimes, with a critical rewiring threshold separating the two phases.

The limitations of purely structural measures become even more evident in multilayer systems, where influence depends on the interplay between layers and temporal dynamics. Using multiplex data from the BBC Pandemic project, Bontorin and De Domenico [306] show that hubs may act as “firewalls” when their activity is distributed across layers, thereby reducing their spreading efficiency. By introducing a notion of temporal distance across layers, they demonstrate that nodes with moderate degree but efficient cross-layer pathways can dominate diffusion. This points to a generalized notion of influence based on the accessibility of dynamical paths, rather than static connectivity alone.

5.2.2. Discursive communities and mediation structures

Since information does not spread on a homogeneous substrate, any plausible model of online information diffusion must be able to explain, or at least accommodate, mesoscale empirical regularities such as discursive communities, mediation structures, and homophilic clusters that selectively expose users to some contents while insulating them from others. In the analysis of online social networks, the term *discursive community* is used to identify groups of individuals contributing to the formation of a common discourse, sharing implicit rules and following a common goal [307,308]. Originally proposed in social science, the term has been extended to the context of online social media, although there is no complete agreement on a perfect translation of the original phenomenon into this novel framework [307].

Using the definition above, a standard “network theory” community structure differs from a discursive community. The former, regardless of the community detection method employed, captures the excess of links inside a group of nodes, while the latter focuses on identifying groups of users gathering around a common set of concepts and ideas. Nevertheless, tools from network theory can be useful to detect discursive communities when appropriately adapted [309].

To detect discursive communities on Twitter, an effective method proposed in the literature revolves around verified accounts [310]. Before its change in ownership in 2022, on Twitter, the identity of the owners of accounts relevant for the public debate was certified autonomously by the platform [311–313]. While the introduction of ‘verified’ users was perceived by some as the introduction of a VIP class of accounts, it was intended to avoid unauthorized impersonations of famous persons on the platform [312]. The verification of an account is graphically depicted as a blue checkmark close to the username. Nevertheless, since late November 2022, the verification of the account can be obtained upon payment as a feature of the Premium account [314]. The main idea of Ref. [310] is to detect similarities among verified users by looking at their audience composed of “standard users”: two accounts contributing to the same discourse should be retweeted by the same standard users. Otherwise stated, the shared discourses are captured as they are perceived by the audience of standard users. With this aim, a bipartite network of verified and unverified users is defined; a link between a standard user and a verified one is present if the former has retweeted at least once the latter. The information about the interaction between these two classes of users is then projected into the layer of verified users: for each couple of verified user the so-obtained co-occurrences capture the number of ‘standard’ users that interacted with both of them. Due to the heterogeneity in the behaviors of verified accounts, the noise removal is a necessary step; therefore, the co-occurrence network is compared with the one obtained by projecting a maximum entropy randomization of the original (bipartite) system. Finally, a statistical validation returns a monopartite binary network among verified users in which a link connects two verified users if the number of common standard retweeters is statistically significant. Then, a community detection is run on the validated network, and the so-obtained labels are propagated to standard users via a label propagation algorithm on the entire retweet network.

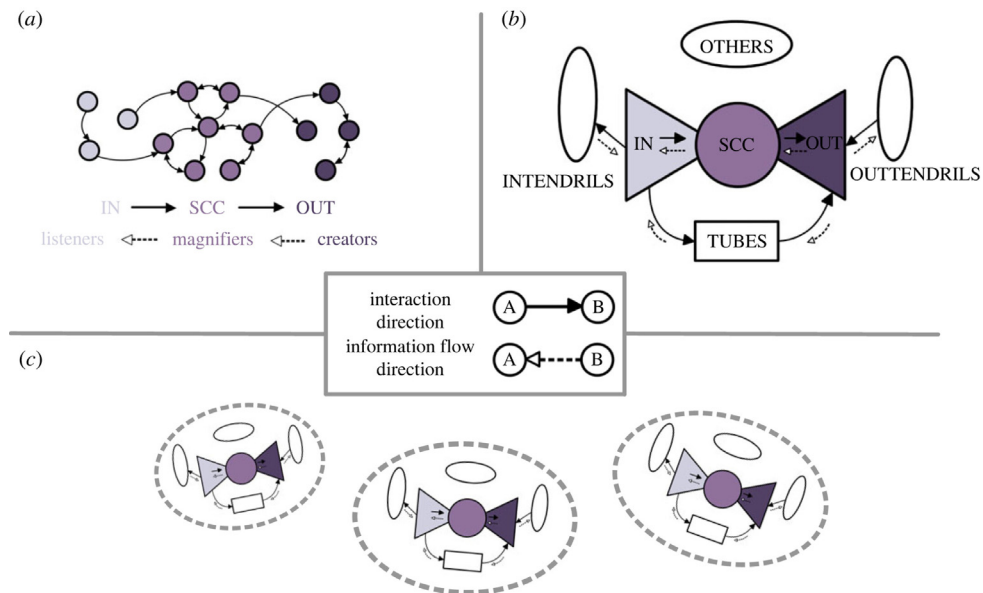


Fig. 5. Mesoscale structures in online social networks. Bow-tie structure in a complex network highlights the organization into a core, identified by a strongly connected component (SCC) where all users can reach each other through information diffusion and peripheral components. The IN component consists of users who can reach the SCC but not vice versa, whereas the OUT component consists of users from whom the SCC can reach but cannot. Tendrils attach to these sub-systems without connecting to the core. See the text for further details.

Source: Figure reproduced from Ref. [319].

Such a framework was applied in multiple cases, providing good results: in political online debates on Twitter, discursive communities align with political coalitions [308,310,315–318]. Furthermore, it was recently observed that verified users are much more efficient as seed for the detection of discursive communities than other class of users based exclusively on the activity [309]: in a sense, it seems that the prestige provided by the verification of an account is particularly relevant in the public debate. Such an observation generates numerous concerns about the opportunity of providing verification checkmarks upon payment.

A notable aspect of this line of work is methodological. Here, statistical-mechanics tools do not primarily enter through a diffusion model, but through the use of maximum-entropy benchmarks and statistically validated projections that separate genuine mesoscale organization from patterns that could arise solely from heterogeneous activity. This makes it possible to identify which structures are informative for diffusion and which are compatible with constrained randomness alone.

Building on this perspective, a recent stream of research has identified a recurring mesoscale pattern in user interactions, known as the bow tie structure [320,321]. Broder et al. [320] originally introduced the bow tie decomposition to characterize the World Wide Web's architecture. Specifically, one first identifies the Largest Strongly Connected Component³ (LSCC); nodes that can access to (but not part of) the LSCC are labeled IN, while those reachable from (but not part of) the LSCC are labeled OUT. Yang and colleagues later refined this classification [321], introducing other blocks in the decomposition. The bow-tie structure is displayed pictorially in Fig. 5. In their depiction of the Web, nodes represented websites and edges represented hyperlinks: the LSCC contained most websites, the IN segment was dominated by search engines, and the OUT segment comprised authoritative sources such as Wikipedia. This framework has since been applied to various systems, including the Tor network [322], the control networks of transnational corporations [323], and more recently, online social platforms [317].

In the context of social networks, it was observed that, when the debate is societal or political, nearly every discursive community exhibits an informative bow tie structure, encompassing nearly all participating accounts. It is natural, at this point to wonder if the observed structure appears by chance and is just due to the different behaviors of the accounts or if it is the effect of something deeper, as the two-step flow mentioned above. The empirical retweet network was then compared with a maximum entropy null model preserving, for each account, the number of different retweeted and retweeting users, i.e. the in- and the out-degree. Results show that the dimension of the blocks in terms of the number of nodes was statistically significant, i.e. it was either too small or too big to be explained by the activity of the users only. In this sense, only looking at the activity of users cannot explain the number of users mediating the information coming

³ The Largest Strongly Connected Component is the largest set of nodes within which each node can reach every other node by following directed edges.

from standard sources [317]. Nodes within the LSCC may be interpreted as opinion leaders, who synthesize messages originating from the authorities in IN and disseminate them to the wider audience in OUT. Motivated by these findings, diffusion models that exploit the bow tie organization of interactions have been proposed [319].

This connection to mediated communication also helps place online diffusion within a broader social-science tradition. According to several scholars, the heterogeneous behaviors exhibited by different accounts may reflect a contemporary version of Lazarsfeld and Katz's "two-step flow" theory [239], in which information does not travel directly from institutional sources to the general public, but is filtered through opinion leaders. Numerous scholars have attempted to adapt this perspective to Online Social Networks, resulting in a variety of interpretations of the opinion leader's role [114,324–328]. Nevertheless, there is no consensus among social scientists regarding the continued significance of the two-step flow in shaping opinions within social networks. For instance, Bennett and Manheim [329] proposed the "one-step flow" theory, suggesting that the primary mechanism for opinion formation lies in platform recommendation systems. Subsequent research has indicated that one-step, two-step, and even more complex multi-step flows can coexist within the same communication ecosystem [326].

5.2.3. Echo chambers, homophily, and platform effects

Another robust empirical pattern at the mesoscale is the emergence of homophilic and weakly interacting communities that bias exposure and constrain diffusion. Several empirical analyses of large-scale Facebook data, in fact, highlight how the circulation of both scientific information and conspiracy-like content is shaped by the emergence of echo chambers, whose separation increased, for instance, between the 2016 and 2020 U.S. elections. In political discourse, users with similar political leanings often form their opinions based on the same news sources [330,331]. Although this phenomenon is unsurprising—many outlets openly disclose their political orientation—it can become problematic when opinions become highly polarized and diverge markedly (even if there are some specific counterexamples [332]). In this scenario, *echo chambers* emerge: they are clusters of accounts sharing identical viewpoints, accepting only information that aligns with their preexisting beliefs and showing strong resistance to alternative perspectives [330,331]. While the original concept was articulated qualitatively within social science, subsequent work has translated it into a quantitative framework and validated it across multiple online debates [232,333,334]. In fact, the presence of echo chambers is investigated in several different social platforms, i.e. Facebook [232,333], X/Twitter [318,334] and Reddit [209,335].

Extending the analysis to fact-checking posts from dedicated debunking pages, it was observed that corrective information remains almost entirely confined to the scientific echo chamber: approximately two-thirds of likes on debunking posts come from science-oriented users, and only a small fraction of conspiracy-oriented users engage with such content [333]. Sentiment analysis of comments, based on a supervised classification model, reveals that responses to debunking posts are predominantly negative, regardless of the commenter's orientation. Strikingly, the rare conspiracy users who do interact with debunking tend to increase their subsequent activity within the conspiracy echo chamber, suggesting that exposure to dissenting information can reinforce rather than attenuate prior beliefs. Otherwise stated, results indicate that the spread of misinformation online is essentially due to entrenched structural and cognitive segregation, in which homogeneity and polarization govern the dynamics of both the diffusion of false narratives and the reception of their corrections.

Remarkably, the presence of echo chambers seems to be related to the rules of the social platform. Studying the political discussions on Reddit, it was shown that, although users display preferences for specific communities, political discourse on Reddit is not dominated by highly segregated, homogeneous clusters: cross-community exchanges are common, and interactions frequently occur between users with differing political orientations. This relative openness is attributed to Reddit's topic-based, forum-like architecture, which fosters encounters across ideological lines, in contrast to the feed-driven personalization typical of social networks [209]. Complementing this view, Monti et al. [335] show that, in Reddit news discussions, ideological echo chambers are largely absent, but significant demographic segregation emerges instead, driven by latent traits such as age, gender, and affluence that are not explicitly visible in the platform's interactions. These demographic factors appear to shape users' worldviews and, consequently, the opinions they express, which in turn guide homophilic interaction patterns. The results suggest that affective polarization may stem less from online ideological isolation than from broader societal divides, with platform design and demographic composition jointly influencing the structure of political debate online. Nevertheless, there is a debate ongoing about the presence of echo chambers on Reddit: other studies confirm that there are indeed interactions among different subreddits, but those are negative and do reinforce the idea of a polarized environment in Reddit [210].

Several attempts to overcome the peculiarities of each platform were proposed in the literature. The main idea of these studies is the operationalization of the detection of echo chambers by quantifying two main ingredients: 1) homophily in the interaction networks and 2) bias in information diffusion towards like-minded users. Early data-driven analyses of propaganda networks on Twitter already moved in this direction, showing that polarization patterns, topological clustering, and centrality-based role identification provide useful information about users' exposure and participation in disinformation diffusion [336].

Instead, in [318], the authors extend such a framework by incorporating maximum-entropy null models into the analysis of the system. Specifically, homophily is detected using the concept of discursive communities [310], while non-trivial biases in information diffusion are assessed following the approach of Ref. [337]. Notably, such a methodology allows different positions to emerge naturally from the data, without the need to predefine them or constrain the

analysis to two mutually exclusive views. Furthermore, the use of rigorous statistical benchmarks, implemented as maximum-entropy null models for complex networks, ensures that only genuine signals are retained for analysis.

In [334], the authors show that platforms like Facebook and Twitter, which are organized around social networks and news feed algorithms, exhibit a clear segregation of users into homophilic clusters, where a user's leaning strongly correlates with their neighbors' average leaning. In these platforms, information spreading is biased, meaning users are more likely to be reached by content from those with similar leanings. In contrast, platforms like Reddit and Gab display a more homogeneous community structure with users not splitting into opposing groups, though the overall leaning may be biased towards one political extreme. A direct comparison of news consumption on Facebook and Reddit confirms this finding, with Facebook showing a higher degree of segregation. These differences highlight the role of platform-specific features, such as feed algorithms, in shaping online social dynamics and influencing the emergence of echo chambers. However, empirical evidence also indicates that, while homophily-driven interactions lead to segregated clusters, exposure to diverse information is limited primarily by user behavior rather than algorithmic filtering alone [203].

5.2.4. Modeling mesoscale constraints on diffusion

These empirical regularities have motivated several modeling strategies. Some approaches treat homophily and ideological leaning as constraints on the pathways available to contagion, while others make cognitive filtering explicit.

In [334], to quantify homophily, the leaning of a user is correlated with the average leaning of their neighborhood, while information diffusion is modeled using a Susceptible–Infected–Recovered (SIR) model to gauge how a user's leaning affects the polarization of their influence set.

Cognitive biases play a fundamental role in shaping misinformation adoption and propagation. Physics-inspired models typically incorporate these biases as heterogeneous node-level parameters that modify susceptibility to misinformation or thresholds for belief adoption. Such heterogeneities introduce disorder analogous to quenched randomness in statistical mechanics [338].

Confirmation bias, where individuals preferentially process information aligning with prior beliefs, can be modeled through bounded-confidence mechanisms. In Deffuant-type models, agents only interact when their opinions differ by less than a tolerance threshold, representing cognitive openness. Low tolerance values lead to fragmentation and polarization—an emergent phase characterized by multiple stable opinion clusters that resist convergence.

Sobkowicz [338] extends this approach by incorporating Bayesian belief updating filtered through personal biases, introducing nonlinearity and multistability where the system can settle into distinct fixed points depending on initial conditions and bias distributions. This resembles random-field Ising models with frustration and glassy dynamics, where disorder prevents global consensus. Moreover, biases introduce memory effects such as the continued influence effect, where misinformation persists even after correction, reflecting non-Markovian dynamics and hysteresis that require multi-compartment frameworks to capture accurately.

The impact of mesoscale structures on spreading dynamics has been extensively investigated through extensions of classical rumor and epidemic models. Clustered topologies enhance local propagation via social reinforcement mechanisms, whereby repeated exposures within tightly connected groups accelerate adoption [339]. This behavior is characteristic of complex contagion processes, in which multiple confirmations are required for activation.

A unifying modeling framework is provided by approaches that explicitly control the level of inter-community mixing. Su et al. [340] introduce a parameter μ governing the fraction of inter-community links, revealing the existence of an optimal intermediate regime that maximizes global cascades. For low μ , diffusion remains localized; for high μ , the loss of reinforcement reduces spreading efficiency. This non-monotonic behavior highlights the dual role of modularity as both a barrier to and an enabler of diffusion.

These theoretical predictions are supported by empirical studies of real systems. Davis et al. [341] report topology-dependent phase transitions in rumor dynamics, with highly clustered networks requiring larger spreading rates to sustain global cascades. Similarly, analyses of Twitter cascades [342] show that community structure strongly constrains diffusion: hubs confined within a single module tend to trap information, whereas nodes embedded in the network core facilitate inter-community spreading.

These studies support a coherent interpretation of network structure in online diffusion. Mesoscale organization is not merely a static backdrop: it shapes who mediates information, which exposures count as reinforcing, how strongly diffusion is confined within ideologically or discursively homogeneous groups, and whether cascades can escape their community of origin. At the same time, the empirical evidence shows substantial variation across platforms, indicating that these structural effects are not universal outcomes of social media use, but depend on the interaction between user behavior, platform affordances, and the architecture of visibility.

This also clarifies the role played here by statistical-mechanics ideas. In some cases they provide null benchmarks that reveal non-trivial discursive, mediation, or homophilic structures; in others they provide dynamical models of inter-community mixing, biased exposure, and clustered spreading. In this sense, physics contributes both by identifying which structural patterns are statistically informative and by formalizing how these patterns alter the pathways and outcomes of diffusion.

5.3. Temporal, multilayer, and higher-order dimensions of diffusion

A further empirical question concerns when static, pairwise representations cease to be sufficient to describe information spreading. In online information ecosystems, diffusion unfolds over time, across multiple platforms and modalities, and often under forms of reinforcement that depend not only on network topology, but also on coordinated exposures, collective attention, and the semantic or emotional organization of content. These ingredients do not simply add realism to otherwise standard models: they can qualitatively reshape cascade timing, effective thresholds, and the very pathways through which information propagates. For this reason, the literature has progressively extended single-layer and pairwise descriptions towards temporal, multilayer, and higher-order frameworks.

5.3.1. Temporal heterogeneity and adaptive dynamics

A natural starting point is the temporal organization of diffusion. The temporal dimension of social interactions plays a decisive role in shaping diffusion dynamics, since the networks on which contagion unfolds are not static backdrops but themselves evolve alongside the behaviors they mediate. Social media platforms change in size and structure, debates flare up and fade, and communities fracture or merge, meaning that the topology of connections is co-determined with the processes of influence and opinion formation. A key question is therefore whether the timescale of contagion is short enough for the network to be treated as fixed, or whether the evolution of the network must be explicitly modeled [343,344].

When these two timescales are comparable, adaptive-network models become essential, as feedback between spreading dynamics and network evolution can create self-reinforcing polarization. For instance, Baumann et al. [345] proposed a feedback loop where individuals preferentially align with similar others, a mechanism that amplifies opinion segregation. Extending mathematical tools from static to adaptive networks has become an active line of research, with mean-field approximations tested for accuracy across population densities [346–349]. Yet most adaptive frameworks remain limited to evolving link weights, while in social systems node turnover—the entry and exit of users—may be equally central. Capturing this within tractable analytical models, beyond agent-based simulations, remains a key open challenge.

Even when the topology can be approximated as static over the lifetime of a cascade, the timing of individual activities strongly affects which exposures become effective. Such activity patterns are consistently found to be bursty and memory-dependent rather than memoryless. Notably, simulations based on Poissonian activation fail to capture these features, whereas SIS dynamics on temporal networks with heavy-tailed inter-event times successfully reproduce them. This provides strong evidence that memory effects in human activity—i.e., non-Markovian inter-event times—are essential for realistic spreading dynamics [350]. The lack of a comprehensive theoretical framework linking memory kernels to epidemic thresholds and points to a significant open problem and a promising direction for future research.

These findings complement earlier threshold-model results showing that bursty contact dynamics can sometimes accelerate, rather than suppress, social contagion [275,276]. More generally, they indicate that temporal ordering is not a secondary detail but part of the mechanism that selects which exposures become effective.

5.3.2. Multilayer and multiplex spreading

If temporal heterogeneity already shows the limits of static network pictures, an additional limitation emerges when diffusion does not remain confined to a single interaction layer. Information propagation, in fact, seldom occurs within isolated platforms. Users frequently inhabit multiple online environments (e.g., Twitter, Facebook, WhatsApp), with information flowing between these interconnected systems. From a network physics perspective, this scenario is optimally modeled using multilayer or multiplex networks [41,47,351–356], where each layer represents a distinct platform, and inter-layer edges capture cross-platform user activity.

In such multilayer frameworks, information spreads both within and across layers through fundamentally different mechanisms. A narrative originating on one platform may cross over to mainstream platforms via bridge nodes—users active on multiple platforms—who function as inter-layer links in the multiplex structure. Xian et al. [357] analyzed misinformation dynamics on correlated multilayer networks, demonstrating that inter-layer correlations and degree heterogeneity systematically lower the effective outbreak threshold β_c , thereby facilitating global cascade formation across the entire multiplex system.

Analytically, multilayer spreading can be modeled through coupled differential equations or message-passing frameworks that explicitly account for both intra-layer and inter-layer transmission processes. The effective reproduction number in such systems aggregates contributions from each individual layer and their mutual interactions. Critically, epidemic thresholds and phase transitions can shift dramatically due to inter-layer coupling: independent subcritical spreading processes within isolated layers can collectively produce supercritical cascades when coupled, analogous to the interdependent percolation transitions observed in infrastructure networks [232,358–360]. From a structural perspective, multiplex networks introduce higher-order correlations and coupling effects that fundamentally modify percolation properties. The presence of overlapping hub nodes across multiple layers creates structural vulnerabilities that function as super-spreader bridges, dramatically accelerating cross-platform contagion. Targeted interventions on such critical bridge nodes—analogue to immunizing high-degree nodes in single-layer networks—can therefore significantly hinder cross-platform information propagation [361,362].

Non-Markovian considerations become even more complex in multilayer systems, where timing mismatches across communication channels can alter diffusion trajectories. Masoomy et al. [363], studying face-to-face and digital interactions in the BBC Pandemic dataset, introduced a multi-pathway temporal distance metric to quantify cross-layer flows. They showed that targeted removal of hubs in one layer could substantially delay or suppress outbreaks in the multiplex as a whole, underscoring the interdependence of different communication modalities. However, the scarcity of large-scale empirical multiplex data with synchronized timestamps remains a major obstacle, limiting the extent to which such models can be validated. Even so, their work demonstrates that effective intervention strategies must account for the temporal coordination across layers, not just within them.

Multiplexity is not limited to the coexistence of different platforms. Contemporary information frequently propagates through multimodal content that combines text, images, audio, and video elements. From a physics perspective, this introduces interacting contagions across distinct information channels, akin to the one observed in epidemics [354], which can be naturally modeled using network representations.

Each modality can be conceptualized as a distinct network layer, with information propagating separately yet interacting synergistically across these parallel channels. Wu and Chen [364] developed a comprehensive analytical framework for such coupled spreading processes, revealing that while individual modality layers may remain subcritical in isolation, their mutual interaction can drive system-wide cascade formation. Simultaneous exposure via multiple modalities—such as text and images—can reinforce belief adoption through cognitive redundancy, effectively increasing the overall transmissibility β_{eff} of the composite contagion process.

This multimodal synergy can be formalized using coupled differential equations or message-passing algorithms across multiplex layers, incorporating explicit cross-modality reinforcement terms that capture the enhanced persuasive power of coordinated multimedia messaging. These multimodal interactions function as coupling constants in the effective Hamiltonian describing the system's spreading dynamics, systematically modifying the phase diagram and critical thresholds of information outbreak formation [359,360].

From a percolation theory standpoint, multimodal content enhances information redundancy: when information fails to propagate successfully via one modality channel, it may still succeed through alternative pathways. This redundancy systematically lowers the effective percolation threshold, analogous to reinforcement mechanisms observed in interdependent network systems. For misinformation intervention strategies, recognizing modality-specific dominance becomes critically important. Physics-inspired models can parameterize channel-specific transmissibilities (e.g., β_{text} , β_{video} , β_{audio}) and optimize mitigation efforts accordingly, with targeted interventions on the most effective channel—the dominant layer in multiplex terminology—potentially achieving disproportionate reductions in overall misinformation spread [361,362].

5.3.3. Semantic and affective higher-order organization

Beyond traditional multiplex models, multimodal content can admit hypergraph representations, where group interactions—such as simultaneous exposure to video and text within group messaging contexts—are modeled as higher-order hyperedges connecting multiple nodes simultaneously [365–367]. Hypergraphs typically express relations involving more than just two individuals simultaneously, thus moving the topological constraints of the contagion mechanism to the representation of the underlying network [368]. However, it is important to note that the notion of “higher-order” interactions does not necessarily require abandoning graph-based representations, since multivariate interactions can be naturally encoded on graphs through appropriate functional forms defined on node neighborhoods [369]. While hypergraph parametrizations can highlight specific interaction mechanisms, many of the reported collective effects—such as nonlinear spreading and abrupt phase transitions—originate from multivariate interaction functions rather than from the hypergraph structure itself, and can be equivalently reproduced within standard graph-based or multilayer network formulations. In the literature adopting the hypergraph representation, Ref. [370] discusses model selection between various hypergraph models of social spreading.

Higher-order organization is not only structural. It may also arise from the semantic and affective arrangement of content itself, which changes how users process, remember, and retransmit information. Beyond statistical regularities, higher-order structures such as narratives provide the semantic scaffolding through which information is processed and shared [371–374]. Narratives impose coherent ordering on facts and events, linking them into storylines that fundamentally shape collective understanding. Well-structured stories exploit cognitive heuristics such as availability bias [375], enhancing processing fluency and perceived plausibility. This makes narrative-embedded disinformation particularly potent: fluency and coherence generate trust [376], while confirmation bias [241,377] promotes selective adoption of content aligned with pre-existing beliefs. Consequently, narrative-driven disinformation spreads differently from epidemic contagion, forming polarized “narrative communities” or echo chambers [333,378] where reinforcing stories circulate with minimal opposition.

Emotional dynamics further amplify these higher-order effects. Research consistently demonstrates that emotionally charged content—whether positive (awe, joy) or negative (fear, disgust, outrage)—exhibits enhanced contagiousness [244, 379–381]. Emotional arousal blurs fact-fiction distinctions, intensifying narrative “transportation” [382] and increasing susceptibility to misinformation [383]. Crucially, corrective counter-narratives achieve maximum effectiveness when they themselves engage emotional responses [384], highlighting that narratives and emotions, as higher-order organizing principles, modulate information flows in ways that exceed the explanatory scope of epidemic-like contagion models.

What emerges from these studies is that temporal heterogeneity, multilayer coupling, and higher-order organization are not peripheral corrections to standard diffusion models. They alter which exposures matter, how spreading synchronizes across channels, and when pairwise static descriptions break down. At the same time, the empirical support is uneven across mechanisms: bursty activity and cross-layer timing effects are already strongly grounded in data, whereas broader claims about universality and criticality are better treated as candidate characterizations of cascade statistics than as settled properties of online diffusion itself.

5.4. Characterizing and predicting diffusion cascades

Besides identifying the mechanisms and structural constraints of diffusion, an important line of work focuses on the cascades themselves as empirical objects to be characterized, compared, and, when possible, predicted. This perspective asks different questions from those addressed in the previous subsections: rather than primarily asking which microscopic mechanism generates spreading, it asks which aggregate regularities can be extracted from cascade data, whether these regularities are stable across contexts, and which observables carry predictive information about future growth.

5.4.1. Temporal profiles, collective attention, and directional signals

A first relevant class of observables concerns the temporal profile of cascades. Even when temporal heterogeneity is treated as part of the spreading mechanism, cascade durations and attention trajectories can also be studied as empirical signatures in their own right. Cascade durations in bursty networks collapse onto a universal scaling curve when time is rescaled by the mean inter-event interval, reproducing the heavy-tailed distributions observed in email and online forum data. Notably, simulations based on Poissonian activation fail to capture these features, whereas SIS dynamics on temporal networks with heavy-tailed inter-event times successfully reproduce them. This provides strong evidence that memory effects in human activity—i.e., non-Markovian inter-event times—are essential for realistic spreading dynamics [350].

A related manifestation of temporal organization is collective attention, where the relevant object is no longer just the transmission path of a single piece of information, but the competition among many items for a limited and time-dependent pool of attention. The dynamics of collective attention reveal additional layers of cognitive constraint on information diffusion. Lorenz-Spreen et al. [56] analyzed competition among cultural items for finite attention resources, demonstrating that content trajectories are accelerating with steeper gradients and shorter life cycles, reflecting saturation of human attention under increasing content production. Complementing this picture, Gravino et al. [385] investigated the coupled dynamics of news supply and user demand during the COVID-19 pandemic, showing that attention is not only a limiting resource but also co-evolves with information production, with questionable sources disproportionately adapting their output to fluctuations in collective demand. Similarly, Eom et al. [386] modeled daily political tweet volumes via geometric Brownian motion, showing that when averaged over optimal time windows, collective attention reliably predicts electoral outcomes.

Global-scale attention dynamics were illustrated in studies of Twitter activity surrounding the Higgs boson discovery announcement [21], where activation probabilities increased with repeated neighbor exposures, producing epidemic-like attention bursts. The “preferential attention” model [57] incorporated heterogeneity in network connectivity and individual reactivity, with response probabilities scaling as $q_i(t) \sim k_i^\alpha$. This mechanism successfully reproduced sharp activity spikes, revealing that influential network hubs disproportionately drive collective attention through multilayer reinforcement effects that amplify sudden visibility surges.

Temporal information can also be used more directly to extract directional organization from cascade data. In this sense, time is not only a source of heterogeneity, but also an observable through which latent coordination patterns can be inferred. Strikingly, directional couplings inferred from temporal activity data can act as early-warning indicators of large-scale coordination, emerging well before the onset of macroscopic activity. This illustrates how temporal causality, rather than static correlations, can uncover hidden organizing principles and provide predictive insight into collective dynamics. For instance, Borge-Holthoefer et al. [51] applied symbolic transfer entropy to Twitter data collected during political protests, converting sequences of user activity into symbolic states and calculating directional couplings T_{ij} between users: comparing the observed transfer-entropy networks against time-shuffled null models revealed statistically significant pre-protest information flows ($p < 10^{-4}$).

5.4.2. Scale invariance, criticality, and universality

A second class of studies asks whether cascade statistics display forms of scale invariance or cross-platform regularity. Here the goal is less to model a specific spreading mechanism than to determine whether different systems share common statistical signatures. In line with the perspective adopted throughout this review, these approaches are best regarded as candidate characterizations of cascade statistics rather than uniformly established descriptions of online diffusion.

At criticality, cascade dynamics are scale-invariant, meaning that both small and very large events occur without a characteristic size. Empirically, this manifests in the heavy-tailed distributions of cascade sizes and durations observed in social media activity. These distributions typically follow power laws,

$$P(S) \sim S^{-\tau}, \quad P(T) \sim T^{-\alpha}, \quad (17)$$

with no obvious cutoff [179,387]. Such algebraic behavior signals proximity to a critical point and aligns with the theory of absorbing-phase transitions. Importantly, hyperscaling relations impose consistency across critical exponents, linking

average cascade size to duration as $\langle S \rangle \sim T^\gamma$, where $\gamma = (\alpha - 1)/(\tau - 1)$ [170,388]. Different values of the exponents τ, α, γ allow researchers to classify spreading phenomena into distinct universality classes.

These exponents are universal properties of the underlying dynamical process: very different systems may exhibit identical critical exponents, despite differing microscopic rules. Classical examples in physics include the Ising and percolation universality classes [170,388]. For social spreading, mean-field contagion processes on sparse networks yield branching-process exponents ($\tau = 3/2, \alpha = 2$) [179], while threshold-based or complex contagion models may fall into universality classes reminiscent of the random-field Ising model [19].

The theoretical elegance of multiplex spreading models is exemplified by their capacity to produce universal scaling behaviors that transcend platform-specific details. O'Brien et al. [389] mapped meme propagation across multiplex networks to multitype branching processes, where each platform or communication channel forms a distinct layer contributing to the overall offspring distribution of information cascades. Within this mathematical framework, large-scale cascades emerge when the largest eigenvalue of the next-generation matrix reaches the critical value unity ($\Lambda_{\max} = 1$), yielding a universal cascade-size distribution characterized by a robust power-law exponent of $-3/2$.

A compelling demonstration of universality in social contagion is provided by Notarmuzi et al. [390], who coupled a Random Field Ising Model (RFIM) with Belief Propagation. Their model included semantic fields (h_i) biasing users' sharing propensities, along with social interactions (J_{ij}). Analyzing datasets from Telegram, Twitter, and Weibo, they observed that once cascade sizes were rescaled by platform-specific averages, the distributions collapsed onto a universal $s^{-3/2}$ law, consistent with critical branching processes. This remarkable data collapse across platforms indicates a shared universality class, despite vast differences in network structures and user behavior. Moreover, the authors demonstrated that randomizing semantic-field assignments destroyed the $3/2$ scaling, highlighting the central role of semantic bias in driving universality. While these findings strongly support critical behavior in online spreading, the authors note that a full Renormalization-Group derivation for heterogeneous networks remains an open challenge.

Complementary evidence comes from Hall and Bialek [391], who applied a maximum-entropy inference framework to small Twitter communities of roughly 100 users. Treating user activity as binary spins ($s_i = \pm 1$), they inferred an Ising Hamiltonian reproducing observed one- and two-point correlations. Their analysis revealed that empirical couplings (J_{ij}) positioned these communities within 5% of a critical temperature T_c , suggesting maximal susceptibility. Near-criticality was further confirmed by significantly larger empirical correlation lengths compared to null models ($p < 10^{-5}$). These results provide strong evidence that social media groups may self-organize near critical states, thereby maximizing responsiveness to small perturbations and generating heavy-tailed cascade statistics.

Building on these insights, Alodjants et al. [392] proposed the “social laser” (solaser) model, a mean-field approximation for viral outbreaks in online platforms. In this framework, the system's magnetization $m(t)$ reflects the global activity level, driven by external media pumping (P) and peer-influence coupling (λ). Viral “lasing” occurs when λ surpasses a critical threshold, directly paralleling epidemic models. Simulations on configuration-model graphs calibrated to Twitter degree distributions confirmed the model's scaling predictions, illustrating how collective peer influence drives transitions to widespread adoption.

Criticality and universality also connect to synchronization models of consensus and polarization. Pluchino et al. [393] introduced an “opinion changing rate” (OCR) model based on a modified Kuramoto framework, where synchronization corresponds to consensus and clustered synchronization to polarization. Extensions, such as bounded-confidence couplings on a Möbius-strip [394] or high-dimensional Kuramoto-type models on opinion spheres [395], demonstrate how consensus, polarization, or dissensus emerge from microscopic interactions. These frameworks complement cascade-based approaches by capturing how critical dynamics may manifest as sudden synchronization or divergence of opinions.

Finally, Delvenne et al. [60] provided a broader methodological framework to quantify relaxation times in stochastic processes on temporal networks. Their approach unifies models ranging from Kuramoto oscillators to SIR epidemics, allowing heterogeneity in parameters and revealing how chain reactions of activations propagate across complex systems. Together, these studies highlight that social spreading phenomena—whether cascades, consensus formation, or viral outbreaks—often operate near criticality, exhibiting universal signatures that transcend specific contexts.

At the same time, empirical evidence for well-defined universality classes in information diffusion remains limited, and often depends sensitively on the choice of observables, the level of coarse-graining, and the temporal window over which cascades are analyzed. The practical application of these elegant theoretical frameworks is further constrained by limited empirical access to comprehensive data on inter-platform dependencies and cross-layer coupling strengths, which are often proprietary and closely guarded by platform operators [396].

5.4.3. Predictive and data-driven approaches

A partly separate line of work prioritizes predictive performance over mechanistic interpretation. These approaches are valuable for forecasting cascade growth, but their relation to interpretable spreading mechanisms is often indirect unless combined with explicit dynamical assumptions.

Random walk methods such as DeepCas [397] and CasWarn [398] model diffusion paths while capturing temporal and structural adoption features. Graph neural networks further enrich this perspective: DeepInf [399] predicts adoption probabilities from local subgraph structure, CasGCN [400] models cascade growth via graph convolutions, and DyDiff-VAE [401] incorporates evolving user interests through dynamic latent variables.

Complementing these machine-learning approaches, differential-equation-based methods explicitly link adoption kinetics to spatio-temporal processes. Wang et al. [402] developed ODID to model temporal-spatial diffusion on Digg,

Cheng et al. [403] combined probabilistic diffusion with neural ODEs for popularity prediction, and Foroozani et al. [404] modeled the anomalous diffusion patterns observed in real cascade data.

These methods broaden the methodological landscape of information-diffusion research. Even when their explanatory content is limited, they provide useful forecasting benchmarks and highlight which temporal, structural, or behavioral signals are most informative for prediction. At the same time, their scientific value is strongest when they can be related back to the mechanisms discussed in the surrounding subsections, rather than treated as stand-alone black-box predictors.

Taken together, this literature shows that diffusion cascades can be studied not only as outputs of specific mechanisms, but also as statistical objects with their own temporal profiles, scaling relations, and predictive signatures. This perspective is valuable precisely because it complements the mechanism-centered view adopted in the preceding subsections: it helps identify which aggregate regularities are robust enough to deserve explanation, which observables are informative for forecasting, and where claims of universality remain tentative.

5.5. Misinformation: dynamics, models, and interventions

The empirical and modeling lessons discussed above become especially consequential in the case of misinformation. Reinforcement, homophily, platform mediation, bursty attention, and heterogeneous user roles are all present in generic information diffusion, but in misinformation they interact with asymmetries in credibility assessment, strategic amplification, and corrective interventions. For this reason, misinformation is best treated not simply as another content class, but as a distinct domain in which several spreading mechanisms become simultaneously relevant.

Misinformation constitutes a distinct domain within the broader study of social contagion, not merely as another type of content but as a phenomenon shaped by specific cognitive, algorithmic, and strategic forces. Unlike generic information spreading, misinformation dynamics involve asymmetries in speed and reach, targeted manipulation by both human and automated agents, and systematic amplification through platform infrastructures. The practical urgency of understanding misinformation stems from its documented impacts on public health, democratic processes, and social cohesion, making the development of effective mitigation strategies a critical research priority. This section examines how misinformation diffusion diverges from and interacts with the dynamics of reliable information, reviews the specialized models developed to capture these distinct mechanisms, and surveys intervention strategies grounded in both theoretical insights and empirical evidence.

5.5.1. Empirical foundations: speed, structure, and amplification mechanisms

Empirical studies across more than a decade of Twitter data indicate that false information spreads faster, deeper, and more broadly than truthful content, particularly in political contexts [227]. This speed differential represents a critical departure from neutral diffusion models and reflects the role of novelty and emotional salience—emotions such as fear, disgust, and surprise—in human amplification behavior. Notably, humans are primarily responsible for amplifying false narratives through these psychological mechanisms. However, the landscape becomes more complex when considering automated agents and periods of acute information demand. The epidemic analogy for mixed-quality information—termed *infodemics*—refers to the overflow of information of varying quality that surges across digital and physical environments during periods of acute demand, leading to confusion and behaviors that can harm health and erode trust in authorities [236,237,405–409]. During the COVID-19 pandemic, for instance, Cinelli et al. [405] observed that unreliable sources, often associated with automated accounts, propagated misinformation at rates comparable to reliable outlets, highlighting the need for nuanced modeling approaches that account for both human and automated amplification.

Network analysis reveals that fake news diffusion networks are denser and more retweet-active than traditional news networks. Verified journalists predominantly anchor traditional news, whereas fake news hubs consist of unverified or deceptive accounts [316,410]. Exposure to fake news is concentrated among a small number of users: just 0.1% of accounts were responsible for 80% of fake news dissemination during the 2016 U.S. elections, and 1% consumed 80% of the total volume [228]. This extreme concentration suggests that misinformation networks exhibit structural properties that differ markedly from those governing the spread of reliable information, with implications for both modeling approaches and intervention design.

Social bots, or simply *bots*, are fully or partially automated accounts operating on social media platforms [411–414]. While not always malicious—some automate harmless tasks like posting quotes or timestamps—bots are increasingly exploited to manipulate online conversations and platform dynamics. They can artificially amplify the visibility of content through mass reposting, increasing the chance of content promotion by recommendation algorithms. More advanced bots, often powered by low-cost large language models (LLMs), impersonate genuine users, engage in conversations, disseminate hate speech, and incite verbal aggression [414]. Bots contribute to amplification as secondary actors. While designed to mimic human activity and evade detection [415], their structural traces reveal coordinated campaigns, such as MacronLeaks [416], the Catalan referendum [417], the UK election campaigns after Brexit [418], and Russian interference in the 2016 U.S. elections [419]. Despite typically lacking central network positions, bots can receive disproportionate attention and subtly shape discourse [420].

Beyond direct interactions, bots structure online networks and conversations in subtle ways. Studies such as [315] show that bots often act as central amplifiers within retweet networks, clustering around specific users or topics and creating structural biases in information flow. In the Italian Twitter debate on migration from Northern Africa, bots were found

to predominantly retweet specific human accounts, presumably their “owners”. However, some bot groups amplified multiple human accounts simultaneously, suggesting coordinated “bot squads” organized around shared political agendas, particularly far-right narratives. Similar findings were observed during the Italian elections [421], where interaction networks revealed that bots often form tightly connected clusters, engaging more with other bots while passively receiving interactions from humans. This network configuration enables the phenomenon of “augmented humans”, where ordinary users become influential by being embedded within bot-rich neighborhoods. Bots have also been linked to the early amplification of low-credibility content before it goes viral [422]. A small fraction of accounts—often bots—are responsible for disseminating a disproportionate amount of such content. Specifically, around 6% of accounts were found responsible for spreading over 30% of low-credibility material. Bots tend to mention influential human users to seed and spread misinformation, further distorting information flow and public discourse. For further information about the research on bot detection, a review recently appeared in the literature [423].

The rise of AI-generated or “deepfake” content adds a qualitatively new dimension to these processes. Synthetic media produced by generative models [424,425] can act as high-transmissibility contagion seeds, lowering adoption thresholds and triggering cascades even in otherwise resilient networks. Their diffusion is shaped by a co-evolutionary arms race between generation and detection algorithms [426], well captured by interacting epidemic models and reversible bootstrap percolation frameworks that account for both propagation and corrective interventions [427]. Experiments further show that AI-generated misinformation is often more persuasive than human-generated content [428], effectively raising the transmissibility β assumed in traditional models. Demographic and cognitive factors further influence susceptibility. For instance, users are less effective at detecting deepfake content when evaluating demographically similar subjects [429], creating localized network vulnerabilities analogous to correlated disorder in physics models.

These asymmetries in speed and amplification are further reinforced by the mesoscale structures discussed above, especially discursive communities, bow-tie-like mediation patterns, and echo chambers.

Disinformation campaigns strategically target specific ideological groups to reinforce pre-existing beliefs, often exploiting and amplifying existing patterns of information segregation. Using the procedure described in Ref. [310], researchers studied the exposure to misinformation during the COVID-19 pandemic in Italy [316] across various discursive communities. Examining associated URLs showed that approximately 22% of shared links from right and center-right accounts were categorized as unreliable. Within such networks, content producers (a vocal minority) are distinct from passive consumers who amplify received content [430]. This structural imbalance causes fringe narratives to appear mainstream, fueling infodemics. Collective attention plays a central role in these dynamics [57]. On Twitter/X, the presence of opinion leaders can be translated into a bowtie decomposition of the retweet network, where especially influent individuals mediate between institutional sources and the public. Mattei and collaborators showed that the greatest flows of misinformation are present inside the LSCC (largest strongly connected component) and from LSCC to the OUT block, i.e., respectively among the opinion leaders and from the block of opinion leaders to the one of the big audience [317]. Remarkably, verified users, even in LSCC, share content from low-quality news sources with smaller frequencies than “standard users” [430].

The analysis of aggregated data from 208 million US Facebook users during the 2020 election confirmed that the platform contributes to high ideological segregation in political news consumption [431]. A meaningful corner of the news ecosystem was consumed exclusively by conservatives, and misinformation, identified by Meta’s Third-Party Fact-Checking Program, was concentrated in this conservative corner without a comparable counterpart on the liberal side. Moreover, a prevalence of sources favored by conservative audiences was observed in Facebook’s news ecosystem. This ideological asymmetry to the advantage of the right-leaning ideological slant was also observed when studying the clash of perspectives that arose on Twitter around the Black Lives Matter protests in 2020 [432]. Right-leaning content benefited from an advantage in the attention economy of social media, gaining increased visibility due to social and algorithmic forms of amplification.

During the COVID-19 infodemic in Italy, unlike the concentrated spread seen in the U.S., unreliable sources had limited exposure and engagement, yet polarization emerged across Facebook pages and groups through coordinated content sharing and topical discussions [337]. The URL-sharing diffusion network exhibited a small-world structure, exposing users to both reliable and unreliable information, highlighting that the core challenge lies in how individuals process and act on the information they encounter. Guarino and collaborators rigorously identified homophily through non-trivial similarity among “information diets” in Facebook’s public discourse, described as the mix of reliable and unreliable news sources that users consume on the platform [337]. The authors constructed a bipartite network connecting accounts to the URLs they shared. Using a maximum-entropy null model, they filtered out statistically insignificant connections to exclude random or low-signal interactions. Projecting the validated network onto account and URL layers revealed clusters of users and sources, which consistently aligned with distinct reliability profiles—highlighting polarization in the information diets consumed by different user groups.

On Reddit, the community-based structure creates a unique misinformation environment [433]. Ideologically polarized subreddits act as echo chambers, where group norms reinforce false beliefs. The platform’s upvote/downvote system, though designed to prioritize quality, often amplifies emotionally resonant or conspiratorial content. Disinformation often originates in niche communities before spreading via cross-posting to mainstream subreddits. Reddit’s pseudonymity enables coordinated manipulations like vote brigading and sockpuppetry. However, well-moderated communities (e.g., r/science) offer self-correction mechanisms through comment-thread rebuttals and strict moderation.

Temporal analyses show that misinformation often thrives during moderation gaps and leverages meme formats or AMAs to evade detection. Notably, Reddit's structure permits the "Streisand effect": attempts to debunk misinformation in one subreddit can inadvertently amplify it in others. Despite these challenges, Reddit offers unique insights into self-correcting versus self-reinforcing information ecosystems. Null models on Reddit have primarily focused on detecting echo chambers [209,334,335], revealing how structurally isolated communities sustain disinformation narratives.

Platform design and algorithmic filtering further bias exposure and amplification beyond the network effects arising from user choices and bot activity. Recommendation systems operate as non-uniform external fields in opinion dynamics, reinforcing concordant views and suppressing dissent [434]. This transforms social networks into adaptive, state-dependent systems with feedback loops that can push them towards polarization or fragmentation, akin to hysteresis in magnetic systems. Empirical evidence supports this view: Corsi et al. [435] show that algorithmic amplification disproportionately boosts misinformation sources, effectively turning them into superspreaders and lowering effective epidemic thresholds for misinformation cascades. Social networks encode trust relationships, where nodes represent people, institutions, or ideas, and weighted edges capture degrees of trust or distrust. Manipulation tactics exploit these structures, for example by inflating follower counts or creating artificial associations ("Google bombs") to influence perceptions of popularity or relevance [436].

A fundamental challenge in combating misinformation is the asymmetric competition between spreaders and fact-checkers. Establishing veracity is technically complex [437], and empirical studies show that misinformation is tightly intertwined with partisan media, effectively shaping political agendas [438], while fact-checks struggle to propagate. Economic incentives exacerbate this dynamic: deceptive content attracts high engagement at low production costs [439]. The combination of rapid misinformation spread, concentrated networks of amplifiers (both human and automated), echo chamber effects reinforced by platform algorithms, and the slow, resource-intensive nature of fact-checking creates a structural imbalance that necessitates specialized modeling and intervention strategies.

5.5.2. Models of misinformation dynamics

The distinctive empirical features of misinformation—its faster spreading relative to corrections, the persistence of false beliefs, and the heterogeneous roles of users and platforms—can be naturally framed within extensions of compartmental models. In this class of approaches, individuals transition between discrete states (e.g., susceptible, informed, spreader, corrected), while additional mechanisms are introduced to capture competition between information types, cognitive responses, and external interventions.

A first robust phenomenon is the competition between misinformation and corrective information. Empirically, misinformation often exhibits a transmission advantage, which can lead to its dominance even in the presence of corrections [232]. This effect can be captured by interacting spreading processes, where different information types propagate simultaneously with distinct rates. For instance, models of competing contagions [440] show that the outcome depends sensitively on relative transmission and recovery rates, as well as on network structure. In particular, a faster-spreading strain can dominate unless corrective information reaches a sufficient fraction of the population early in the process, highlighting the importance of timing and early intervention.

In investigating the potential impact of misinformation spread, the multiplex network framework offers a natural and effective description, as it captures the interplay between the diffusion of (dis)information regarding a given phenomenon and other dynamics related to the phenomenon itself.

Early contributions by Lima et al. [441,442] adopting this perspective explicitly coupled epidemic spreading with information dynamics in structured populations. In particular, metapopulation models informed by large-scale mobility and communication data [441,442] describe geographic subpopulations connected through mobility flows and social ties, where disease transmission co-evolves with the dissemination of preventive information. These studies show that, while restricting mobility alone may have limited impact on delaying endemic states, the concurrent spread of information can significantly mitigate epidemic outcomes, highlighting the role of communication channels as effective intervention pathways. Complementarily, a quenched network formulation is introduced by Granell et al. [360], where an SIS epidemic process is coupled to an awareness dynamics on a second layer. Their results reveal the emergence of a metacritical point: below a critical awareness transmission rate, the disease persists endemically, whereas above it, awareness spreading suppresses the epidemic, thus formalizing the threshold-dependent interplay between information and contagion processes.

Building on this line of research, recent work has shifted attention to the specific role of misinformation and behavioral responses. In particular, d'Andrea et al. [443] integrate empirical evidence on risk perception—derived from large-scale survey data—with epidemic modeling, introducing heterogeneous compliance behaviors associated with differing levels of perceived risk. Their results indicate that the presence of a fraction of "risk-denier" individuals, who do not adopt protective measures, can substantially alter epidemic trajectories, increasing both transmission and hospitalization burden. Importantly, the impact of such behavioral heterogeneity is modulated by the underlying contact network structure: modularity and degree heterogeneity can mitigate epidemic peaks for small fractions of non-compliant individuals, yet amplify adverse effects when this fraction becomes large. This highlights how misinformation, by distorting risk perception, can indirectly shape epidemic outcomes through nonlinear interactions between behavior and contact patterns.

Empirical evidence indicates that individual responses to corrections are not neutral, but mediated by cognitive and social factors [444]. Compartmental models incorporating such effects show that corrections may have unintended

consequences. In particular, Tambuscio et al. [445] introduce additional states to account for fact-checking and post-correction behavior, demonstrating the possibility of “backfire effects” in which exposure to corrections reinforces, rather than mitigates, belief in misinformation. This mechanism effectively modifies transition probabilities between compartments, showing that the impact of interventions depends not only on their reach but also on how individuals process them.

Heterogeneity in user roles can be incorporated within the same framework by stratifying compartments according to user types. For example, approaches based on SIR-like dynamics combined with exposure metrics such as the Infodemic Risk Index (IRI) [446] allow one to account for differences between verified users, unverified accounts, and bots. This captures the empirical observation that spreading capacity and susceptibility are unevenly distributed, and that specific classes of users disproportionately contribute to misinformation cascades.

Finally, these modeling ingredients can be combined to study intervention strategies in a unified setting [447]. Simulation-based approaches [448] show that single interventions—such as fact-checking or node removal—often have limited impact when applied in isolation. Instead, combining multiple mechanisms can produce synergistic effects: for example, reducing the influence of key spreaders lowers the effective transmission rate, thereby increasing the efficacy of corrective information. From a compartmental perspective, such strategies act simultaneously on multiple transition channels, altering both spreading and recovery processes. However, these results also highlight that optimal interventions are constrained by external considerations, including legal and ethical limits on actions such as account removal.

Several additional modeling directions extend this compartmental core by incorporating memory, reversibility, and adaptive platform effects.

The persistence of misinformation even after corrective interventions—the “continued influence effect”—necessitates models with non-Markovian memory kernels to capture long-term retention. Standard Markovian models assume that the probability of state transitions depends only on the current state, not on the history of past exposures. However, psychological research demonstrates that individuals often continue to rely on misinformation even after being informed of its falsity, particularly when the misinformation has been integrated into a coherent mental model. Non-Markovian models introduce memory effects, where the probability of accepting or rejecting new information depends on the sequence and timing of prior exposures. These models can capture phenomena such as the primacy effect (early information has disproportionate influence) and the difficulty of dislodging entrenched beliefs.

Reversible bootstrap percolation frameworks [427] provide another approach to modeling misinformation and correction dynamics. In these models, nodes (individuals) adopt a state (belief in misinformation) when a threshold number of neighbors have adopted it, but can also revert to a non-adopting state when exposed to corrective information. The interplay between forward propagation (misinformation spreading) and backward recovery (correction) creates rich phase behavior, including hysteresis, where the system's state depends on its history. This framework is particularly useful for understanding the conditions under which misinformation becomes entrenched and difficult to reverse, even with substantial corrective efforts.

Recent work has begun to incorporate the role of AI-generated content into epidemic models. The high persuasiveness of AI-generated misinformation [428] can be modeled as an increased transmission rate β or reduced adoption threshold in cascade models. The co-evolutionary dynamics between generation and detection algorithms [426] suggest the need for adaptive models where the parameters governing misinformation spread and correction efficacy evolve over time in response to technological and strategic changes. Such models can capture the arms race between those producing synthetic misinformation and those developing tools to detect and counter it.

Finally, models that incorporate platform algorithms and their effects on information flow are essential for understanding modern misinformation dynamics. Algorithmic recommendation systems can be modeled as external fields or bias terms that modify the effective transmission rates between nodes based on content characteristics and user preferences [434]. These models reveal how algorithmic amplification can create feedback loops, where misinformation that initially gains traction receives disproportionate visibility, further accelerating its spread. The empirical finding that algorithmic amplification lowers the effective epidemic threshold for misinformation [435] can be directly incorporated into threshold models and percolation frameworks, providing a mechanistic understanding of how platform design choices influence misinformation prevalence.

Summarizing, these models capture several distinctive ingredients of misinformation dynamics—competition, awareness, heterogeneous user roles, and intervention effects—but their empirical calibration remains challenging, since it depends on operational definitions of misinformation, platform-specific visibility mechanisms, and heterogeneous cognitive responses to corrective actions.

5.5.3. Mitigation strategies

Because misinformation combines rapid diffusion with strong structural and cognitive asymmetries, mitigation strategies have been developed at multiple levels, from monitoring and early detection to interventions on network structure, recommendation systems, and automated amplification.

In the literature, different strategies, based on the structural properties of the various platforms, were proposed to limit the effects of disinformation. These approaches range from monitoring and early detection to structural interventions on networks and information feeds, to technological solutions for identifying automated actors.

On platforms like Twitter, structural asymmetries offer insights into information diffusion. Verified accounts, marked by blue checkmarks, serve as identity anchors within political discourse, often representing key ideological poles (left,

center, right) [309]. Mapping engagement behaviors—follows, retweets, and replies—relative to these verified accounts reveals networked communities that shape public conversations. Projects like politoscope.org exemplify this approach, tracking political discourse in France in real time. By measuring account proximity to misinformation sources via network metrics and semantic analysis (e.g., hashtags), these methods provide a proxy for assessing content exposure [316]. Such monitoring systems enable the early identification of emerging misinformation cascades and the actors most responsible for their propagation, facilitating targeted interventions before narratives become entrenched [449].

Within a complex network, a limited subset of nodes, influencers, plays a determinant role in the interconnection topology since their activation could enable the dissemination of information throughout the entire network. At the same time, their suppression could prevent epidemic diffusion. The optimal influence problem aims at finding the minimal set of influencer nodes for the system at hand and can be exactly mapped onto optimal percolation [299]. The goal is to find the minimum number of nodes necessary to fragment the network. This approach identified a set of influencer nodes displaying low connectivity while retaining strategic links, which were overlooked by other heuristic approaches. Studies on network robustness show that targeted removal of central nodes (e.g., by degree or eigenvalue) can fragment networks and inhibit spread [440], illustrating a theoretical principle often difficult to apply in open social media contexts due to legal, ethical, and practical constraints.

Other strategies to neutralize noxious actors on social platforms involve detecting certain questionable behaviors. However, such malicious behaviors evolve rapidly, making these strategies outdated and ineffective. Recently, BLOC [450], a language framework to encode the behavior of social media users, either bots or humans, has been proposed. The words in this framework are symbols drawn from two alphabets, representing user actions and content. Moreover, to capture timing patterns of content diffusion, BLOC representations are characterized by unsupervised clustering accounts based on behavioral similarity to detect bots. The same framework can also be employed for coordination detection, identifying drivers of information operations that massively target citizens, foreign nationals, organizations, etc.

Detecting automated agents has become an active research field [451,452], with detection tools often integrated into platforms to warn human users about likely bot accounts [453]. However, as detection techniques evolve, so do the evasion strategies employed by bots. Even so, when bots are primarily designed to boost a particular user's posts, their activity patterns often leave detectable traces, despite attempts to camouflage their behavior.

Social bots detection systems can be classified as graph-based, crowdsourcing, and feature-based [412]. Graph-based detection system examples are Facebook Immune System or SybilRank, which are based on the assumption that sybils connect mainly to each other. Crowdsourcing detection is performed by humans, as happens on the Social Turing Test platform: humans are believed to detect bots easily, but the implementation cost is the major limitation of this approach. Feature-based detection employs machine learning techniques to distinguish human-like and bot-like behavior from salient features. This latter class of bot detectors displays among the best performances.

Botometer (recently renamed *Botometer X*) is probably the most famous and used tool for detecting likely automated accounts on X/Twitter [452,454]. Botometer estimates the extent of automation in user accounts, distinguishing spam, fake followers, astroturf bots, etc. Botometer uses hundreds to over a thousand features drawn from multiple dimensions of a user's account. These include profile metadata (e.g., age of account, default profile image, username features), network features (followers/following relationships, clustering, social graph patterns), temporal activity (posting frequency, inter-tweet timing, circadian patterns), content features (lexical richness, sentiment, URLs, hashtags), and interaction patterns (retweets, replies, quoting behavior). The classification is performed using Random Forest classifiers trained on labeled datasets of human versus automated accounts. The output is a score (or set of scores) indicating how “bot-like” an account is, and may also assign probabilities or scores for different types of bots (spammer, fake follower, astroturf, etc.). The bot-detection models and features are periodically updated to adapt to new bot behavior.

Cresci and collaborators address the problem of detecting fake followers on Twitter, i.e. accounts created specifically to inflate the follower counts of target users, using a similar approach [411]. The authors trained and evaluated multiple machine learning classifiers over several annotated datasets, comparing the performance of rule-based methods (e.g., single rules or sets of rules from media) versus feature-based classifiers (drawing from academic feature sets). They showed that many of the media rules perform poorly (low recall, or high error) for fake-follower detection, whereas classifiers using more sophisticated features do much better. Since some features are expensive to collect (especially relationships, neighbors' followers/friends, full timelines), they proposed a lightweight classifier, termed *Class A*, which uses only “cheap” features (i.e., those requiring relatively low API access/crawling cost), still achieving high accuracy (>95%) on their training baseline. Overall, this method demonstrated that a properly selected subset of features can deliver strong detection performance with reduced data-collection cost and that their lightweight classifier is practical for large-scale usage (at least under the data conditions at their time).

Since the ownership change of X/Twitter on October 27, 2022, several changes have affected access to Twitter's data and, therefore, bot detection algorithms functioning in scientific research. For instance, because of restrictive API access, some data that Botometer previously relied upon (e.g., full user timelines, rate of historical tweet retrieval, follower/following graph) may be incomplete or delayed. In some cases, certain endpoints may no longer be accessible or may have severely limited rate limits. Furthermore, as collecting labeled data and maintaining up-to-date ground truth becomes harder under limited access, the ability to update models to detect new bot behavior may lag.

Another possible counteraction consists in structural interventions on the feeds. Removing reshared content from the Facebook feed of a random set of consenting, US-based users during the 2020 US election significantly decreased exposure

to political news, clicks, reactions, and partisan news clicks while also reducing news knowledge within the studied sample [455]. On the other hand, when switching from algorithmic feeds to reverse-chronological feeds on Facebook and Instagram [456], the exposure to political and untrustworthy content increased on both platforms, and the exposure to insulting content decreased on Facebook. In contrast, the exposure to content from moderate, ideologically mixed sources increased. Surprisingly, neither of these treatments had a notable impact on political polarization or individual-level political attitudes.

Analyzing Facebook feeds of the entire population of active adult users in the USA in 2020 [457], it has been confirmed that most of the content consumed comes from like-minded sources. However, political information and news represent only a tiny fraction of these exposures. A possible solution to break these echo-chamber structures would be to modify the social network algorithm to show less like-minded content. Nyhan and coworkers conducted a field experiment among 23,377 users, reducing exposure to like-minded sources by one-third during the 2020 US elections. Exposure to uncivil and misleading content decreased with like-minded content, although users were more likely to interact with it when they encountered it. Moreover, this reduction strategy did not change political attitudes, polarization, and ideological extremity.

Finally, contrary to common beliefs, a possible intervention to mitigate polarization involves introducing anonymity in online political discussions. This has been implemented in a mobile chat platform [458] designed to explore the impact of different levels of anonymity on political discussions. A recent study [459] involved people living in the US from both political alignments, Republicans and Democrats, in discussing a controversial policy issue with an opposing partisan. The results suggested that individuals who engaged in anonymous discussions on the platform experienced significant declines in polarization compared to the control group tasked with writing an essay using identical conversation prompts.

In summary, misinformation provides the clearest case in which the different mechanisms reviewed throughout this section must be combined rather than studied in isolation. Misinformation dynamics emerge from the interplay of human cognition, network topology, platform algorithms, and automated agents. Understanding these mechanisms—and integrating them into predictive, multilayer, and memory-aware models—remains critical for designing interventions and mitigating the societal impact of information disorders. The empirical evidence demonstrates that misinformation is not simply a faster-spreading version of ordinary information; it is amplified by emotional resonance, algorithmic biases, concentrated networks of spreaders, and the strategic use of automated accounts. Models that capture these features—through multiplex structures, backfire effects, non-Markovian memory, and adaptive parameters—provide a foundation for understanding why misinformation is so persistent and difficult to counter. Mitigation strategies must therefore be multi-faceted, combining early detection and monitoring, structural interventions targeting key spreaders and network vulnerabilities, technological tools for bot detection, algorithmic modifications to reduce amplification biases, and carefully designed corrective messaging that accounts for psychological resistance. The challenge remains to translate theoretical insights and simulation results into practical, scalable, and ethically sound interventions that can be deployed across diverse platform environments.

6. Models of opinion dynamics

There are many other scenarios of microscopic mechanisms that create emergent macroscopic social effects. This section will cover some models of such scenarios, all different from social contagion (Section 5) in that every agent has a variable representing an opinion (identity, knowledge, etc.) already from the beginning, but this something changes throughout the evolution of the model. This class of models has been extensively reviewed elsewhere [19,65,67,460–462]. We present here the most salient features of these models and epistemological roles.

Unsurprisingly, physicists have been interested in simple models reminiscent of statistical mechanics. The Sznajd model [463] is, for example, mathematically very close to the Ising model of magnetic phase transitions. The voter model [464,465] and majority vote model [466] are non-equilibrium dynamic models where a randomly distributed starting configuration becomes reorganized during the run of the model to various possible types of emergent configurations, such as locally ordered, globally ordered, and disordered ones. As we will see, each of these configurations brings its own interpretation in sociological terms. The de Groot [467] and Friedkin-Johnsen [468] models could also be included in this context.

Some models have richer representations of whatever spreads: the Axelrod model of cultural dynamics [469,470] has an integer vector representing the state of an individual, the Deffuant model [471] has a continuous variable, etc. Sometimes the state variables trigger a binary decision when they pass a threshold [472–474]. In recent years, moreover, sociophysics-type models of opinion propagation have often been studied on networks where the effect of the network topology has been in focus [295,475,476].

It is important to note that, traditionally, validating these types of models against experimental or observational data has been the exception rather than the rule. Actually, their primary purpose has been to support theorizing and reasoning about emergent social phenomena, rather than to predict them. More recently, there have been calls to focus efforts on developing theoretical frameworks that compare, relate, and integrate the various existing models, while also leveraging empirical data to better ground these models [462,477,478].

In this section, we discuss several families of opinion dynamics models that are particularly relevant from a physics perspective. We first frame the problem by skimming over some facts that we believe should be kept in mind when

approaching the modeling of this type of social phenomenon. Then, we move to discuss different paradigmatic models. We also focus on coevolution models, in which the social network and agents' opinions mutually influence one another. Throughout the section, we examine the impact of complex connectivity patterns on model behavior. Finally, in a dedicated subsection, we address the role of heterogeneous temporal patterns and their influence on the dynamics of the models. Our goal here is not to provide an exhaustive catalog of opinion models, but to highlight a small number of recurrent collective patterns—consensus, polarization, fragmentation, persistence of disagreement, and coevolution with social ties—and to discuss which modeling ingredients have been proposed to account for them.

6.1. Contextualization

Roughly speaking, the basic idea behind modeling opinion dynamics is to provide explanations for how opinions form and change, supported by empirical evidence. Here, we treat the concepts of opinion and belief as synonymous, representing the arbitrarily complex internal states of agents. A fundamental sociological assumption is that human behavior and decision-making are shaped by the set of opinions individuals hold on various matters. However, opinions are not the only contributors to opinion change. For a long time, the social sciences have debated the relative influence of personal traits versus situational factors—a discussion known as the person–situation debate [479]. This debate centers on identifying the most significant predictor of social behavior. While individual traits have been linked to opinions, other influential factors have emerged. Research has shown that personality can predict average behavior, particularly when social influence is minimal.

What is clear, however, is that opinion dynamics are primarily driven by collective effects. It is the complex interplay between agents and their environment that ultimately shapes the trajectory of opinion evolution [480–482]. By acknowledging this interplay, we can draw several parallels between physics and the social sciences. In particular, statistical physics serves as a bridge between the micro and macro levels, explaining macroscopic phenomena that emerge from the interactions of a huge number of particles, for which it is not only virtually impossible to gather accurate individual information but most of this very individual information is actually unnecessary to predict large-scale behaviors [1]. Empirically, it turns out that the average behavior of the particle ensemble is what is most frequently observed. Theoretically, statistical physics offers very accurate predictions for both these average realizations and their fluctuations.

Similarly, in the social sciences, a micro–macro relationship exists. Although providing an accurate description of each individual agent may be infeasible, there remains a meaningful link between micro-level processes—how agents influence one another—and macro-level outcomes, such as the emergence of non-trivial opinion distributions. One of the central goals, then, is to develop quantitative laws that can explain the emergence of these global regularities. This involves understanding both the complex processes through which agents gather information and interact with their peers—typically studied in social psychology—and the resulting structures and dynamics at the societal level.

6.1.1. Types of social influence

There is empirical evidence regarding the social responses of agents that should be taken into account when designing a model of opinion dynamics [483]. One of the most well-documented findings is that an individual's behavior and, by extension, her opinions and beliefs, can be altered when exposed to a source of social influence [484,485]. The most studied and common response to such influence is conformity, which refers to the tendency to align one's opinion with that of others [486].

The concept of conformity encompasses various nuances, but two well-differentiated types are commonly recognized: conversion and compliance [484,487]. Conversion refers to a genuine internal change in beliefs, where the influenced individual adopts the external opinion as their own; see, e.g., [488–490]. In contrast, compliance involves outwardly aligning with the influencing opinion while privately maintaining one's original belief—often due to social pressure or a desire to avoid conflict, rather than true agreement; see, e.g., [491–493].

The opposite social response to conformity is known as nonconformity, which can manifest in different forms [487,494]. The two most well-known types are independence and anticonformity [495]. Independence refers to maintaining one's own opinion regardless of external social influence; the individual neither conforms nor reacts oppositely, but instead relies on personal judgment. Anticonformity, on the other hand, involves deliberately adopting a position that is contrary to the influencing opinion—essentially resisting influence by expressing disagreement, even if doing so is not in line with one's private beliefs.

When modeling opinion dynamics, it is thus important to have in mind which source(s) of social influence we are dealing with, in order to isolate that mechanism from other ones so to understand their effects at the collective level.

6.2. Discrete opinions

Even if the agents can perceive themselves internally in a continuous opinion space for matters, there are many scenarios in which they are constrained to express this opinion by choosing among a finite number of options; see Fig. 6(a). For instance, political views can be very complex but people end up by voting among very few choices.

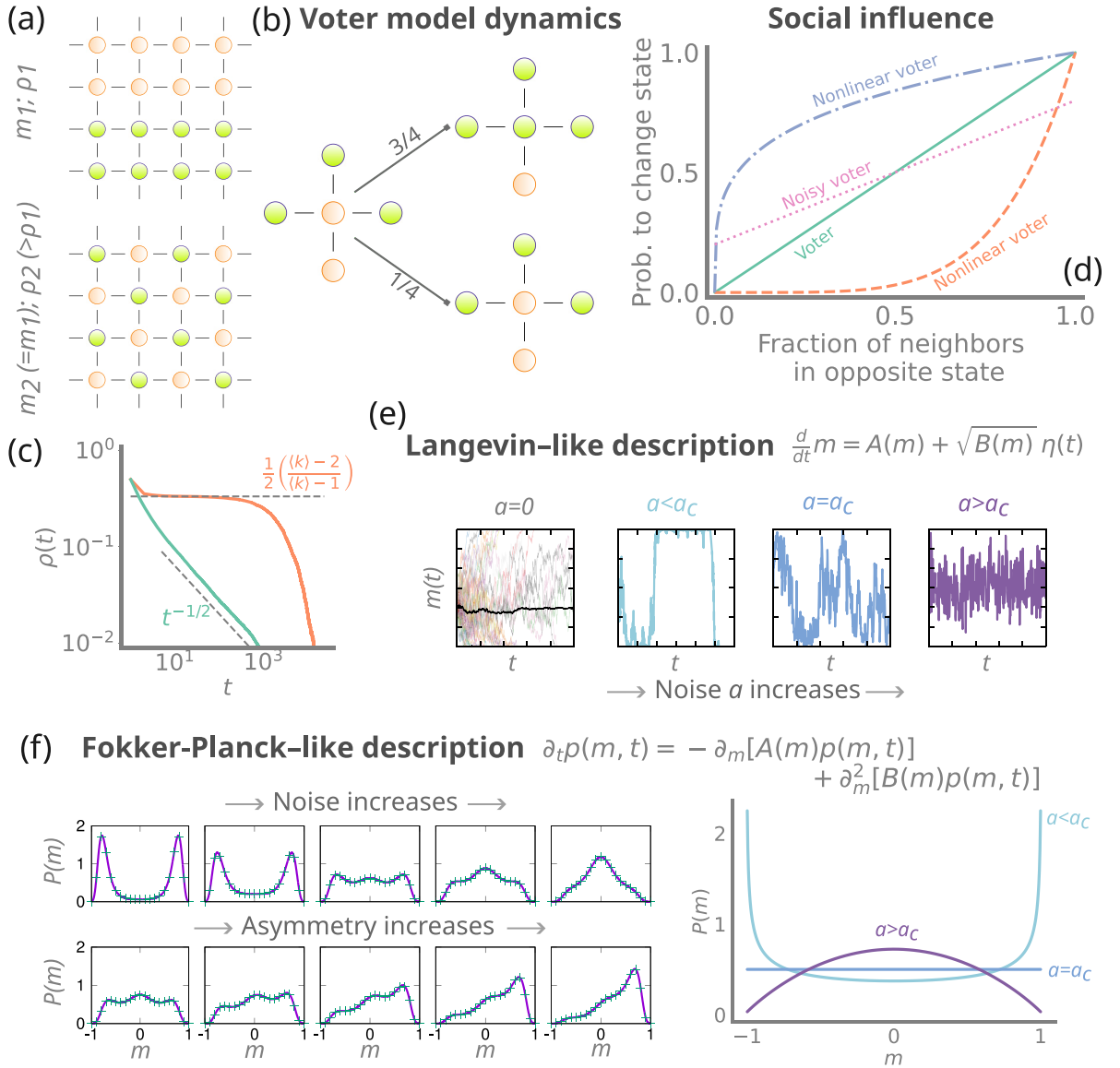


Fig. 6. In (a), sketch representing the logic behind the physically-inspired metrics introduced in the main text to characterize opinion dynamics. In the two regular networks, nodes (agents) can be in any of two states $S_i = \pm 1$, here represented by the two different colors. Both networks have the same value for the magnetization $m = \sum_i S_i/N$, since the proportion of the two opinions is the same. On the contrary, the density of active links ρ measures the level of order in the system, and it is lower in the above network because opinion clusters are larger there. In (b), sketch representing a single update in the voter model. The central agent is chosen to attempt an opinion update and adopts the opinion of a neighbor selected uniformly at random. In this case, it becomes green and orange with probability $3/4$ and $1/4$, respectively. In (c), we display how $\rho(t)$ captures different ways to reach the consensus state, i.e., $|m| = 1$ and $\rho = 0$: either through a coarsening process ($\rho(t) \sim t^{-1/2}$; voter model in a one-dimensional lattice) or through a finite-size fluctuation after the stabilization in a metastable plateau $\rho^{\text{st}} = \frac{1}{2} \frac{(k-2)}{(k-1)}$ for a timescale that grows with N , where (k) is the mean degree of the complex network on top of which the voter model evolves. In (d), we sketch the functional form of the probability for an agent to change state depending on the fraction of her neighbors in the opposite state, for different opinion dynamics models explained in the main text. In (e), we show individual trajectories of the magnetization. For the standard voter model ($a = 0$), 50 independent trajectories are presented, all departing from $m(0) = 1/3$. We can appreciate how the average magnetization is conserved over the ensemble of trajectories (solid line). In the other panels, we show a single trajectory of the noisy voter model in the bimodal ($a < a_c$) and unimodal ($a > a_c$) phase, and one at the critical value of the noise ($a = a_c$). This panel has been adapted from [496]. In (f), the stationary probability distribution for the magnetization $P(m)$ for the nonlinear noisy voter model (with exponent $\alpha = 6$) on the left and for the noisy voter model on the right. In the panels of the top row, the system is kept symmetric and, as noise is increased, we observe a transition from a bimodal to a trimodal distribution and from a trimodal to a unimodal one. In the bottom panels, the noise is kept constant, and the asymmetry is varied. We identify a transition from a trimodal to a bimodal distribution and a transition from a bimodal to a unimodal one. Markers come from numerical simulations, while solid lines are the analytical approximations. This panel has been adapted from [497]. The rightmost plot shows the modality transition for the noisy voter model. Lines correspond to the noise values used in the magnetization trajectories in (e).

6.2.1. The voter model

Models of social response with binary choices have been developed across disciplines, including the Willis symbolic scheme [495], the four-dimensional model [487], and the diamond models [486]. Here we focus on approaches rooted in statistical physics.

A paradigmatic framework is the voter model, a parameter-free binary-opinion model where agents update their state by copying a randomly chosen neighbor. Despite its simplicity, it has broad applications beyond opinion dynamics, including catalytic reactions [498–500], neutral evolution [501–504], probability theory [505–508], and non-equilibrium statistical physics [509–511].

The model evolves through discrete updates: at each step, a randomly selected agent adopts the opinion of a randomly chosen neighbor. Over time, the system may reach an absorbing consensus state, where all agents share the same opinion and dynamics cease. A central question is whether the system converges to a consensus or remains in a fluctuating state.

The outcome strongly depends on the interaction topology. On low-dimensional lattices ($d \leq 2$), the system undergoes coarsening: domains of like-minded agents grow, and the density of disagreeing links $\rho(t)$ decreases over time, driven by interfacial noise [510]. In contrast, for $d > 2$, the system becomes trapped in metastable states, with $\rho(t)$ stabilizing before finite-size fluctuations eventually drive consensus. In the thermodynamic limit ($N \rightarrow \infty$), consensus is no longer reached.

These behaviors are well understood in regular lattices [512] and in mean-field settings [513,514]. Complex networks, effectively high-dimensional structures, exhibit similar qualitative dynamics but differ quantitatively. In particular, lower levels of order and different convergence properties emerge. Analytical approaches such as approximate master equations [179] and pair approximations [515–517] have been developed to study these effects.

Finally, network structure also affects conservation laws [178,518] and consensus times, which depend on the degree distribution moments [465,519]. The full distribution of consensus times can exhibit power-law behavior depending on initial conditions [520].

6.2.2. Group-size effects: the q -voter model and non-linear variations

Mathematically, the voter model is relatively simple, as the probability of an agent changing her opinion increases linearly with the fraction of neighbors holding the opposite opinion; see Fig. 6(b, d). This simplicity, along with the parameter-free nature of the model, makes it a solid foundation upon which more sophisticated or realistic assumptions about social influence can be built. These modifications are typically encoded in the rules governing how agents update their internal state, or alternatively, how the influence exerted by neighbors leads an agent to change her opinion (see Fig. 6(d)).

One such effect relates to group size. As discussed earlier, compliance is frequently observed in social interactions. Experimental research has shown that the impact of compliance is proportional to the size of a unanimous influence group, but only up to a certain threshold. Beyond a group size of approximately five individuals, the effect of additional members yields diminishing returns [521–523]. Moreover, compliance is significantly reduced when the group of influence is not unanimous, highlighting the importance of perceived consensus in social influence [522,523].

One of the most paradigmatic models that include group effects is the q -voter model [524]. It encapsulates the idea of unanimity, in which the social pressure on an agent is effective only if she confronts several times with her neighbors and finds the same opinion all the times, after which she adopts that opinion. Sometimes, the model is endowed with some noise, encoded in a constant probability ϵ to change state if the q verifications did not result in the same opinion. The properties of the q -voter model have been extensively studied over the years, for example, its probability of reaching consensus [525–529], the time needed to reach consensus [528], and the effects of the network topology in the phase diagram [528]. For a review, see [530].

From a more general perspective, the social influence mechanism of the q -voter model can be understood as a deviation from the linear peer influence assumed in the standard voter model. This deviation is formalized in the class of nonlinear voter models, which account for scenarios where the dependence on opinion frequency is not linear [531,532].

More specifically, in nonlinear models, the probability that an agent switches opinion is proportional to a continuous power α of the fraction of neighbors holding the opposite opinion. This framework enables the modeling of various types of group influence on agent opinion changes: for instance, for $\alpha > 1$ results in a convex opinion-switching probability, meaning that agents are less influenced by their peers in opposite opinion or, alternatively, more resistant to changing opinion than in the standard voter model case. On the other hand, $\alpha < 1$ models the opposite behavior: agents have a higher propensity and preference to change opinion upon interaction with contrary-minded agents; see Fig. 6(d). Introducing such nonlinearity gives rise to a rich physical phenomenology. In particular, the stationary distribution of the system's magnetization (i.e., the net opinion balance) can undergo modality transitions, including the emergence of bimodal or unimodal distributions, and may exhibit a tricritical point, where the nature of the phase transition changes [497]; see Fig. 6(f).

Beyond opinion dynamics, this type of group-size-based nonlinearity has been applied in other areas of sociophysics, such as language dynamics, where similar mechanisms govern language competition and evolution [533,534].

6.2.3. Idiosyncratic choices: the noisy voter model

Complementing group-based influences, there are mechanisms in decision-making and opinion formation that do not depend on the states of neighboring agents, yet have been extensively incorporated into opinion dynamics models. From a social perspective, such influences can be motivated by factors like idiosyncratic choices or mass media effects [535,536]. From a physics-inspired viewpoint, these mechanisms are often referred to as noise or temperature, analogous to their role in thermal phase transitions. We adopt this latter nomenclature here.

The effects of noise in binary-state stochastic models have been widely studied. Introducing noise into the voter update rules results in a model that is isomorphic to several well-known systems in complex dynamics, such as the Kirman model [537–539], which has been used to explain heterogeneous trading strategies and bounded rationality in behavioral financial models, as well as in models of surface-catalytic reactions [540,541]. In terms of the transition rates for opinion changes, these remain linear as in the standard voter model, but with a smaller slope, due to the nonzero probability of changing opinion when the agent agrees with all her neighbors and the less-than-one probability of changing opinion when all the neighbors are in the opposite state; see Fig. 6(d).

Idiosyncratic opinion changes in opinion dynamics yield a phenomenology fundamentally different from that of the standard voter model. Most notably, absorbing states are eliminated, and ergodicity is restored. This results in a non-trivial non-equilibrium steady state, whose properties depend strongly on the balance between social herding and individual idiosyncratic behavior.

When noisy (random) updates are rare, the system tends to remain near consensus states for long periods of time, with occasional excursions away from consensus. The time scale of these excursions is much smaller than the time the system spends near consensus. As the noise level increases, such excursions become more frequent, eventually leading to a situation in which all opinion configurations are approximately equally likely. Beyond a critical noise level, the system self-organizes around a state of perfect opinion coexistence. In Fig. 6(e), we display individual trajectories of the magnetization in the different regimes, alongside the typical trajectories for the noiseless case $a = 0$, i.e., the standard voter model. In the right panel of Fig. 6(f), through the stationary distribution of the magnetization, the three regimes can be easily appreciated.

This behavior reflects a modality transition, from a bimodal regime (where probability concentrates near consensus states) to a unimodal regime (where probability peaks around zero magnetization). The transition point is inversely proportional to the number of agents N in the system. Consequently, as N increases, the likelihood of observing the bimodal phase, and hence the transition, decreases [542–545].

6.2.4. Mathematical treatment

The mathematical treatment of all the variations of the voter model described here, and others, can be approached with tools developed to study stochastic processes [546]. In particular, the most widespread approaches are the Langevin and Fokker–Planck descriptions, obtained by performing the proper approximations to the master equation. Let S_i be the opinion of agent i , which we take $+1$ or -1 in the binary settings described in this section. In a single step δt of the dynamics, three events can occur. If the chosen agent changes opinion, the magnetization can increase by an amount $\delta m = 2/N$ in the case of the transition $S_i = -1 \rightarrow S_i = 1$ or decrease the same amount if $S_i = 1 \rightarrow S_i = -1$ occurs. If there is no opinion change, $S_i = \pm 1 \rightarrow S_i = \pm 1$, the magnetization remains constant. Denoting these first two processes by $R(m) \equiv \text{Prob}\{m \rightarrow m + \delta m\}$ and $L(m) \equiv \text{Prob}\{m \rightarrow m - \delta m\}$, the last one reads $\text{Prob}\{m \rightarrow m\} = 1 - R(m) - L(m)$, due to probability conservation. If $p(m, t)$ stands for the probability of observing the system with magnetization m at time t , we have [519]

$$\begin{aligned} p(m, t + \delta t) = & R(m - \delta m)p(m - \delta m, t) \\ & + L(m + \delta m)p(m + \delta m, t) \\ & + [1 - R(m) - L(m)]p(m, t), \end{aligned} \quad (18)$$

where $\delta t = 1/N$ is typically chosen so N updates result into one Monte Carlo step. Expanding Eq. (18) to first order in time and to second order in magnetization, we obtain the Fokker–Planck equation:

$$\frac{\partial p(m, t)}{\partial t} = \frac{\partial}{\partial m} [A(m)p(m, t)] + \frac{\partial^2}{\partial m^2} [B(m)p(m, t)], \quad (19)$$

where

$$A(m) \equiv \frac{\delta m}{\delta t} [R(m) - L(m)] \quad (20)$$

is the drift term and

$$B(m) \equiv \frac{1}{2} \frac{\delta m^2}{\delta t} [R(m) + L(m)], \quad (21)$$

is the diffusion term.

Using the well-known relation between the Fokker–Planck and the Langevin equation, we can write down

$$\frac{d}{dt} m = A(m) + \sqrt{B(m)} \eta(t), \quad (22)$$

Table 4

Drift $A(m)$ and diffusion $B(m)$ functions of three variants of the voter model as functions of magnetization $m \in [-1, 1]$. a denotes the noise strength in the noisy voter model. α is the nonlinear flipping probability. In Itô sense, these drift and diffusion are related to the Fokker–Planck and Langevin equation such that $\partial_t p(m, t) = -\partial_m [A(m)p(m, t)] + \partial_m^2 [B(m)p(m, t)]$ and $\frac{d}{dt}m = A(m) + \sqrt{B(m)}\eta(t)$, respectively. Here $\eta(t)$ is a Gaussian white noise.

Model	Drift $A(m)$	Diffusion $B(m)$
VM	0	$\frac{1}{2N}(1 - m^2)$
Noisy VM	$-\frac{a}{2}m$	$\frac{1}{N}\left[a + \frac{1-a}{2}(1 - m^2)\right]$
Nonlinear VM	$2^{-\alpha}(1 - m^2)[(1 + m)^{\alpha-1} - (1 - m)^{\alpha-1}]$	$\frac{1}{N}2^{-\alpha}(1 - m^2)[(1 + m)^{\alpha-1} + (1 - m)^{\alpha-1}]$

where $\eta(t)$ is a Gaussian white noise. These stochastic descriptions of opinion dynamics models allow one to unveil where it is more probable to find the system in the opinion space (consensus, perfect coexistence of opinions, etc.) as well as to address the first passage statistics between different opinion configurations [520].

In light of this, the mathematical description of binary-state opinion dynamics models boils down to identifying what the probabilities $R(m)$ and $L(m)$ are. For instance, for the limit of large $N \gg 1$, in the voter model we have [513]

$$\begin{aligned}
 R(m) &\equiv \text{Prob}\{m \rightarrow m + \delta m\} = \frac{1}{4}(1 - m^2) \\
 L(m) &\equiv \text{Prob}\{m \rightarrow m - \delta m\} = \frac{1}{4}(1 - m^2) \\
 \text{Prob}\{m \rightarrow m\} &= 1 - R(m) - L(m) = \frac{1}{2}(1 + m^2).
 \end{aligned}$$

A summary of the drift and diffusion terms for the models discussed here is given in Table 4.

6.2.5. Other discrete opinion models

Here, we have reviewed the voter model and two of its most prominent variations, in which modifications to the transition rules are implemented to capture different types of social influence. Other variations of the voter model, based on alternative forms of social influence that agents can experience, have been extensively discussed in the literature, including formulations with committed or stubborn minorities that can sustain disagreement and reshape the route to consensus [547]. Further details can be found in the reviews [548,549] and the references therein.

The unconditional social influence assumed in the voter model is a reasonable approximation in situations where agents blindly trust their peers or where there is no mechanism for evaluating the reliability or popularity of opinions. However, the voter model's blind copy mechanism is not universal and in many empirical scenarios other mechanisms of opinion change are at play. One alternative is the majority rule model, which was originally introduced as a model for hierarchical voting in societies [550], and later applied to opinion dynamics [551] to explain the spread and eventual dominance of minority opinions under specific conditions.

In its original formulation, the majority rule model for opinion dynamics assumes a population of agents, each holding an opinion, say, without loss of generality, $+1$ or -1 . Agents interact within so-called meeting cells, whose sizes, i.e., the number of agents participating in a discussion, follow a given distribution and are fixed at the beginning of each independent realization of the dynamics.

At each time step, agents are randomly assigned to meeting cells, and all agents within the same cell adopt the opinion of the local majority. This is a process reflecting assimilative influence, and can be interpreted as a deliberation in which the group must collectively voice a single, agreed-upon opinion, which is always that of the majority.

A key mechanism by which a minority opinion may spread is through social inertia [552], namely, a bias that manifests as resistance to change or reform. In the event of a tie within a cell, one opinion is adopted by default; this is typically set arbitrarily, for instance, in favor of opinion $+1$.

A striking and counterintuitive result is that an initially minority opinion, i.e., when fewer than half of the agents hold opinion $+1$, can ultimately dominate the public discourse. Put otherwise, the initial minority becomes the consensus majority over time, leading to a bottom-up rejection of the opinion originally supported by the majority. This convergence to consensus occurs on a time scale proportional to $\ln N$, where N is again the number of agents [553].

Another central model in opinion dynamics is the Sznajd model [463], whose dynamics are inspired by social impact theory. In this model, a group of neighboring agents is selected. In its original formulation, the model was studied on a one-dimensional lattice, where pairs of adjacent agents were chosen. Later extensions to two-dimensional lattices involved selecting groups of neighboring agents arranged in plaquettes [554].

If the selected group of agents shares the same opinion, it is assumed that they are able to convince their immediate neighbors, who then update their opinions to align with that of the group. Conversely, if the selected group is not in agreement, their neighbors retain their original opinions.

Although both the majority rule model and the Sznajd model lead to a consensus in the long run, there are manifest differences between both of them, regarding the directionality of influence. In the majority rule model, influence flows inward, from the surrounding neighbors to the central agent or group. In contrast, in the Sznajd model, influence flows outward, spreading from a central, unified group to its neighbors.

6.3. Continuous opinion

As anticipated, there are scenarios in which a finite number of opinions cannot represent certain social phenomena well, and we need to allow agents to hold opinions in a continuous spectrum. At odds with discrete opinions, dealing with continuous ones opens the possibility that interacting agents reach compromises among them, resulting in asymptotic configurations that cannot be obtained in the discrete setting. Similarly, the mechanisms of social influence operate differently in the case of continuous opinions. These mechanisms are approached with the so-called models of assimilative and similarity-biased influence, that encompass agents gradually adjusting their opinion upon interaction. The particularity is that interactions are restricted under the bounded confidence condition, i.e. agents need to be close enough in the opinion space to influence each other. In these terms, bounded confidence is a sort of homophilic relation.

The basic assumptions to treat mathematically continuous opinion dynamics are to work with an opinion space $S \subset \mathbb{R}$ and with the agents' opinions $\mathbf{x}(t) \in S^N$, where N is the number of agents. Without loss of generality, the typical choice is $S = [0, 1]$, i.e., opinion values are normalized to unity. Note that generalization to multidimensional continuous variables $S \subset \mathbb{R}^d$ and $S = [0, 1]^d$ is also possible, yet one must take into account how the different opinion dimensions influence each other [555]. Two alternative viewpoints for the dynamics of the opinions predominate in the literature [556]. The first one, the agent-based approach, provides a discrete map $\mathbf{x}(t+1) = f(\mathbf{x}(t), t)$ that specifies how each agent i updates her opinion x_i . Complementarily, the density-based approach [557] employs the density function $P(x, t)$, such that $P(x, t)dx$ is the fraction of agents that have opinions in the range $[x, x+dx]$ at time t . The ultimate goal is to find empirically-grounded rules behind the temporal evolution of $P(x, t)$ that are able to explain the experimental data and predict unknown scenarios to be tested in new experiments.

There are two main models that have been studied in the literature that assume continuous opinions that evolve through the bounded confidence of the agents. Both of them were introduced at the turn of the century, yet in very different contexts. The Deffuant–Weisbuch (DW) model [471,558] was developed within an EU project for the improvement of agri-environmental policies. The other, the so-called Hegselmann–Krause (HK) model [559], was first introduced as a nonlinear version of older consensus models [467]. Their main difference is rooted in the social influence mechanism. In the former, interactions are pairwise and symmetric, meaning that agents i and j , upon interacting, influence each other and their opinions becomes closer. In the latter, agent i takes the average opinion of all the agents that are in her confidence interval.

6.3.1. The deffuant–weisbuch model

Let us focus first in the DW model. At each time step, two interacting agents i and j are selected. The discrete map for the DW reads

$$\begin{aligned} x_i(t+1) &= x_i(t) + \mu [x_j(t) - x_i(t)], \\ x_j(t+1) &= x_j(t) + \mu [x_i(t) - x_j(t)] \end{aligned} \quad (23)$$

as far as $|x_i(t) - x_j(t)| \leq \epsilon$; otherwise $x_i(t)$ and $x_j(t)$ remain unchanged. Here, $\mu \in (0, 0.5]$ is sometimes called persuasiveness or persuasibility, and $\epsilon \in [0, 1]$ is the so-called confidence or tolerance parameter. Hence, i and j 's opinions become simultaneously similar to each other if both agents hold an opinion that, in the first place, is close enough in the opinion space. Given an initial condition $\mathbf{x}(0)$, the system evolves towards an absorbing state in which exists full consensus $x_i(t \rightarrow \infty) = x^*$, $\forall i$, or fragmented clusters with local consensus values whose separation in the opinion space is larger than ϵ [560]. The possible states to which $x_i(t)$ can tend are displayed in Fig. 7(a)–(c). The goal, therefore, is to determine in which configuration the system ends up given the initial distribution of opinions $\mathbf{x}(0)$, the network of interactions and the parameters of the model.

The alternative density-based approach facilitates the analytical treatment, as well as reduces the computational effort as far as one is not interested in the effects of small population sizes. In the DW model, one finds [561]

$$\begin{aligned} \frac{\partial P(x, t)}{\partial t} &= \frac{1}{\mu} \int_{|x-y| < \epsilon} P(y, t) P\left(y + \frac{1}{\mu}(x-y), t\right) dy \\ &\quad - \int_{|x-y| < \epsilon} P(x, t) P(y, t) dy. \end{aligned} \quad (24)$$

This is simply a master equation, with a gain and a loss term, accounting for the expected number of agents whose opinions respectively enters in and leaves out the opinion interval $[x, x+dx]$ in dt . Alternative forms of the master equation for the DW model can be found in Refs. [556,557].

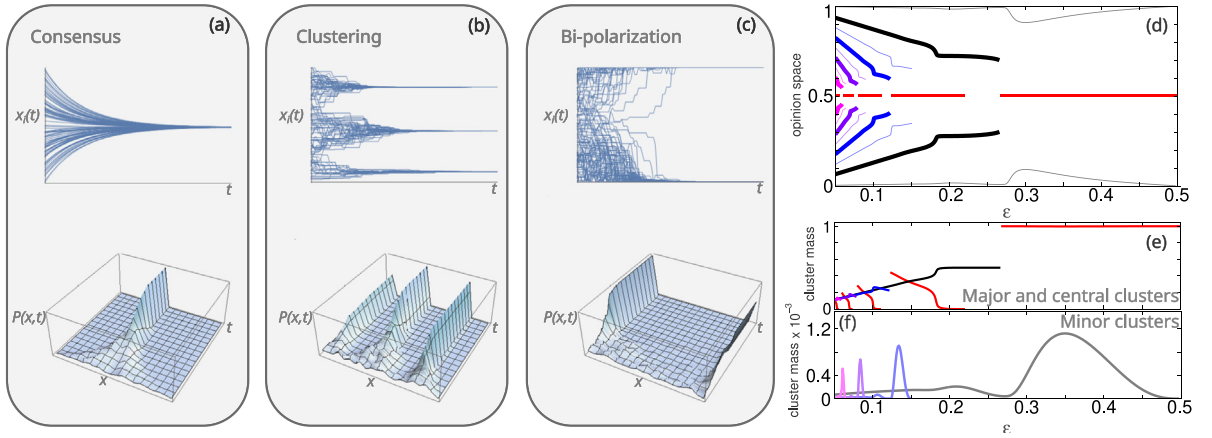


Fig. 7. Possible outcomes for the Deffuant–Weisbuch continuous-opinion model as a function of the tolerance parameter ϵ : (a) consensus, with all nodes sharing the same opinion; (b) clustering into several intermediate opinions; (c) polarization in two extremes of the opinion space. On the right, panel (d) shows the bifurcation diagram for the DF model: the position of the opinion cluster(s) is presented as a function of the tolerance parameter. Thick lines correspond to the clusters formed by the majority of agents, while thinner lines indicate the location of clusters that, even with a finite number of agents, are not the majority. (e) and (f) show the masses of the related clusters. Notice the existence of minor clusters at the extreme opinions and between the locations of major clusters.

Source: Panels (a), (b) and (c) have been adapted from [462], and (d), (e), and (f) from [556].

Note that Eq. (24) assumes a well-mixed population, where all agents can virtually interact with the entire network. However, it has been recently reported that the network of interactions of the agents impacts the dynamics of the DW model, leading to outcomes that are potentially different from those predicted by the mean-field equation [562]. For instance, on Erdős–Rényi graphs the number of stable opinion clusters grows as the confidence bound decreases. In contrast, on cycle graphs, the confidence bound has no influence, and the population ultimately reaches a unanimous opinion. The dynamics on other network types, such as lattices [471] or Barabasi–Albert [563] and Watts–Strogatz networks [564], also exhibit different behaviors compared to complete graphs. Notably, it was not until recently that the limiting, all-to-all assumption has been lifted from the analytical treatments. In Refs. [561,565], degree-based mean-field equations are proposed for the evolution of the probabilities $P_k(x, t)$, standing for the fraction of agents of degree k with opinion x at time t .

As can be readily seen from Eq. (23), the opinion displacement is weighted by the persuasiveness μ of one agent into the other. (As a matter of fact, μ can be equivalently interpreted as the amount an agent is willing to change its opinion upon a successful interaction). It essentially determines the speed of convergence towards the absorbing state and, as a result, plays a role in influencing the final number of clusters [566,567]. Specifically, when μ takes on intermediate or large values, convergence occurs rapidly at the extremes of the opinion spectrum. This can lead to a few agents remaining isolated in those regions, unable to communicate with the rest of the population. Hence, they retain their initial opinion and form two small extremist clusters close to $x = 0$ and 1 . In contrast, when the persuasiveness is small, the convergence is slower, and all agents have the chance to interact and be influenced by others, gradually aligning their opinions with the larger clusters over time.

The other key parameter of the DW model is the confidence ϵ , and it also controls the number of clusters at the absorbing state. When all agents share the same confidence parameter $\epsilon_i = \epsilon$, $\forall i$, we talk about the homogeneous scenario; otherwise, we are in the so-called heterogeneous setting. Intuitively, we can expect that the more open-minded agents are, the less likely will be to find polarized configurations. Indeed, this expectation is verified, on average, for initial opinions that are distributed uniformly at random and agents with a confidence $\epsilon \geq 0.5$: full consensus is reached at the intermediate opinion value. For $\epsilon < 0.5$, a richer phenomenology appears, with several clusters of different sizes emerging.

To capture the location of these clusters and to understand where the system of agents polarizes, bifurcation diagrams are used; see Fig. 7(d)–(f). They mark the opinion of the clusters as a function of the confidence ϵ , and help identify at which ϵ -values clusters emerge or split. These bifurcations have been reported to occur in non-trivial ways [557]. In particular, four fundamental types of bifurcation behavior repeat in decreasing order of ϵ and across progressively smaller ϵ intervals. For instance, as already hinted, for $\epsilon \geq 0.5$, a single large central cluster forms, encompassing most of the population. As ϵ drops below 0.5 , two minor clusters begin to emerge near the boundaries of the opinion spectrum. Around $\epsilon \approx 0.266$, the central cluster splits into two major clusters. As ϵ continues to decrease, the central cluster reappears as a minor cluster at approximately $\epsilon \approx 0.222$, and then rapidly gains mass around $\epsilon \approx 0.182$, pushing the two major clusters further apart. This behavior keeps repeating over and over as the confidence is decreased. A scaling of these intervals with $1/\epsilon$ has been deemed plausible, based on the numerical evidence.

The location of the stationary clusters mentioned above is delta-peaked, namely, $P_{st} = \sum_{i=1}^r m_i \delta(x - x_i)$, where r is the number of clusters, x_i is the opinion of cluster i and m_i is the fraction of agents in cluster i , also known as its mass. As far as noise is introduced in the DW model, stationary clusters display a certain width with respect x_i , hence bifurcation diagrams are constructed by reporting the maximum opinion value within the cluster. Moreover, because of noise, the agreement between theory and simulations may be compromised [568,569]. The initial opinion distribution has also been reported to play an important role in the final configuration of the clusters, which can force or prevent consensus [569].

The intriguing simplicity of DW model has converted it into a reference model on top of which further influence mechanisms have been incorporated. One is algorithmic bias [570], where agents are selected to interact more frequently if they are closer in the opinion space, mimicking recommendation systems of online media. Incorporating such an effect leads to an increased tendency to opinion fragmentation, increased polarization and, counterintuitively, longer convergence times to the steady state [570]. Adaptive and heterogeneous confidence bounds have been found to lead to fewer major opinion clusters and longer convergence times than the baseline DW model [571]. Finally, longer times to achieve consensus, as well as more opinion fragmentation with respect to the baseline model, have also been reported if agents are assigned a heterogeneously distributed activity level that mediates the probability of being chosen for interaction [572].

Another context in which the DW model has been employed is when agents need to form a consensual product, in which, on top of the pairwise agent influence, a global (indirect) interaction is mediated through a medium that holds and modifies its opinion. Notably, this can display transitions between consensus and perpetual conflict, qualitatively agreeing with consensus formation in Wikipedia [573].

6.3.2. The Hegselmann–Krause model

At odds with the pairwise influence of the DW model, the opinion influence in the Hegselmann–Krause model is interpreted as a higher-order effect among all the neighboring agents within the confidence intervals. Denoting by $\mathcal{N}_i$ the neighborhood of node i , the agent-based updates for the HK model are recursively written as

$$x_i(t+1) = \frac{1}{|\mathcal{I}_i(t)|} \sum_{j \in \mathcal{I}_i(t)} x_j(t), \quad (25)$$

where $\mathcal{I}_i(t) = \{j \in \mathcal{N}_i \mid |x_j(t) - x_i(t)| < \epsilon\}$ is the confidence set of agent i at time t , i.e., the set of neighbors whose opinions lie within ϵ of agent i 's opinion. At each time step all agents update simultaneously: each agent i sets its new opinion equal to the arithmetic mean of the opinions $x_j(t)$ of the agents in $\mathcal{I}_i(t)$. However, in [574], a version of the HK model has been proposed to interpolate between the fully synchronous and asynchronous case by incorporating agent stubbornness. Note, moreover, that when the confidence parameter ϵ tends to 1, the bounded confidence models introduced here reduce to the well-known (unweighted) DeGroot model [467].

A density-based description of the dynamics of the HK model can be obtained in a similar way to that of the DW model (Eq. (24)), i.e., through a master equation that individuates the gain-loss terms [556]. Let us define the vector of individual confidences $\epsilon = (\epsilon_1, \dots, \epsilon_N)$. In this setting of heterogeneous confidences, the confidence set $\mathcal{I}_i(t)$ includes all neighbors j for which $|x_i(t) - x_j(t)| < \epsilon_i$. Let us also define the ϵ -local mean

$$M_1(x, \epsilon) = \frac{\int_{x-\epsilon}^{x+\epsilon} y P(y, t) dy}{\int_{x-\epsilon}^{x+\epsilon} P(y, t) dy}. \quad (26)$$

This function gives the expected value of the fraction of agents whose opinion is within the interval $[x - \epsilon, x + \epsilon]$. For a homogeneous bound of confidence $\epsilon = [\epsilon_1, \epsilon_2]$, the time evolution of the density function reads [556]

$$\begin{aligned} \frac{\partial}{\partial t} P(x, t) = & \int_S dy [\delta(M_1(y, \epsilon) - x) P(y, t) \\ & - \delta(M_1(x, \epsilon) - y) P(x, t)]. \end{aligned} \quad (27)$$

Again, this is a gain-loss equation, where the first and the second δ -terms in the integral indicate, respectively, the fraction of agents that transition into, and leave from, opinion x . The generalization of Eq. (27) to heterogeneous confidence levels follows directly [556].

The distribution of the opinion clusters in the HK model has been reported to be highly sensitive to the initial conditions and the interaction thresholds [556,559,575]. Some regularities emerge, though. For instance, in the all-to-all case, global consensus is reached for $\epsilon > \epsilon_c$, where $\epsilon_c \sim 0.2$. Surprisingly, the value of $\epsilon_c \sim 0.2$ is quite robust, as far as the mean degree of the network diverges when we take the limit $N \rightarrow \infty$. In networks where $\langle k \rangle$ remains finite, one gets $\epsilon_c \sim 1/2$ when the same limit is taken [576]. Cluster splitting occurs through bifurcations as a function of the confidence level. Notably, signatures of dynamical phase transitions, like critical slowing down, have been reported near these bifurcations [577]. However, when not all neighboring agents are treated equally and, instead, one weighs most on the opinion of the neighbors that is not shared by others, these opinion cluster bifurcations disappear, and final consensus is always guaranteed [578].

A myriad of generalizations to the Hegselmann–Krauss model have been explored in order to account for a broader range of social situations it can model. One is to include multi-dimensional opinion spaces, even though this generalization

leads to similar qualitative behavior as far as the higher-dimensional confidence area is symmetric, e.g., a circle or a square in two-dimensional opinion spaces [579–581]. Another family of variations concerns in modifying the updates rules, for instance, to take into account external influences [582] and environmental or communication noise among agents [583]. Fuzzy logic has been used to model interaction ambiguity among agents [584]. Interactions mediated in time has been explored too, for instance, with the incorporation of decaying confidence [585] or distance-dependent interaction weight [586]. The concept of bounded influence, in contraposition to the bounded confidence, has been explored in Ref. [587]. In such a model, interactions are mediated by the confidence parameter of the neighbor and not the focal node's one, i.e., $\mathcal{I}_i(t) = \{j \in \mathcal{N}_i \mid |x_j(t) - x_i(t)| < \epsilon_j\}$. Finally, in [588] it has been explored the case where agents hold some resources that are used when opinion changes, hence modeling scenarios in which changing opinion require some effort. The inclusion of the cost of opinion change leads to interesting phenomenology, such as a re-entrant phase transition between global consensus and cluster fragmentation with well-defined critical exponents.

6.4. Flocking-inspired opinion dynamics models

We close this section by emphasizing the parallels between opinion dynamics and the seemingly unrelated problem of flocking. In recent years, non-equilibrium statistical physics has sought to explain the phenomenology underlying the collective motion of animals and active matter [589]. Flocking models are inherently spatial: agents move in physical space and align their headings by averaging those of neighboring agents. In flocking models, however, neighborhoods are defined by spatial proximity, typically via a fixed interaction radius or a set number of nearest neighbors.

The study of flocking can inform both continuous and discrete opinion dynamics models, and vice versa. For instance, in the classical Vicsek model [58], agents move at constant speed and, at each time step, update their heading to the mean heading of neighbors within the interaction radius, subject to stochastic noise. This can be mapped to a noisy Hegselmann–Krause model, where the confidence parameter ϵ plays the role of the interaction radius. On the other hand, local averaging is not always observed empirically; instead, voter-like copying mechanisms are sometimes more appropriate [590]. In this context, the multistate voter model with imperfect copying can be mapped to a discrete version of a flocking model; this has been studied for both finite [591] and infinite [592] interaction radii. Overall, the transition from a disordered to an ordered flock is mediated by the level of noise in the copying mechanism. This mirrors results from consensus formation in purely opinion-based models and underscores, once again, the central role of idiosyncratic choices in the emergence of macroscopic patterns.

A common feature of most flocking models is a rapidly changing interaction topology induced by spatial motion. Spatial embedding both constrains interaction patterns and is itself altered by the evolving states, producing a bidirectional feedback absent from the opinion models discussed so far in this section. Depending on the social system under study, the assumption of a static topology may not always be empirically accurate, and important phenomenological features may be overlooked. In the next section, we examine this coupling between state dynamics and network structure in the so-called co-evolving network opinion models. For further details on the continuous opinion dynamics models discussed here and other variations, we refer to the reviews [66,67,556,593–595] and references therein.

6.5. Coevolution of opinions and social structure and fragmentation transitions

A key element that has been shown to critically impact the behavior of opinion dynamics models is the structure of the interactions between agents [596]. Traditional models were proposed either in low-dimensional lattices, oftentimes drawing inspiration from statistical physics spin-like models [597], or in the all-to-all regime, where all agents interact can interact among them. Yet, contact patterns both in online and offline social contexts are more complex, displaying several features such as high levels of heterogeneity in the number of connections, homophilic and assortative relations and hierarchical community structures. In the previous sections, we have already hinted at the novel phenomenology that can emerge due to the non-trivial social structure, but we have assumed throughout that networks were static. When studying opinion dynamics, in certain situations, this may be justified because the timescales for network rewiring can be much longer than those of the unfolding social process. At the other extreme, we have processes for which the focus is on how the network evolves but the information of the state of the nodes is not deemed relevant and completely disregarded. However, the conditions assumed by these two extreme cases are rarely met in empirical scenarios, and we need models that help us addressing the situation in which the timescales for network re-adaption are similar to the inner scales of the opinion dynamics. Furthermore, both processes can influence each other, leading to highly nontrivial outcomes. The study of coevolving dynamics is, at least, as old as the field of network science, yet in its origin it was mainly inspired by biological problems, e.g., see [598–601], and the review [602]. However, the topology-dynamics feedback mechanisms are general and can also be framed in the precise context of opinion dynamics (Fig. 8).

Most coevolving opinion models assume an underlying social influence mechanism operating among agents, coupled to a probabilistically link rewiring when certain conditions are met. Through the combination of both elements, opinion-based network fragmentation is observed. Actually, the emergence and maintenance of fragmented outcomes normally occur through a nonequilibrium transition with nontrivial time scalings [605,606]. Even if there are several choices for the network restructuring rules and the opinion dynamics model has been proposed in the literature, the transition from full consensus inside a single connected component of agents to a fragmented society with isolated groups holding different opinions has been proved to be robust [604].

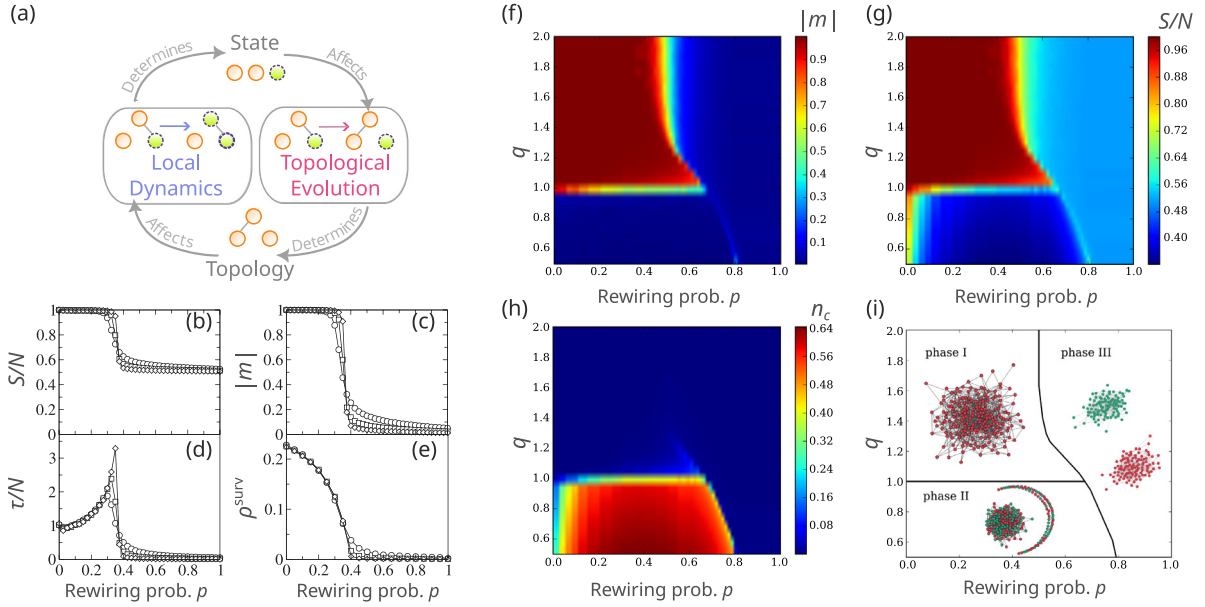


Fig. 8. (a) Sketch showing the feedback logic between state and structure changes in coevolving adaptive processes. In (b)–(d), different metrics are used to characterize the fragmentation transition as a function of the rewiring probability p for the coevolving voter model introduced in the text: normalized size of the largest connected component S (b), absolute value of the magnetization $|m|$ (c), normalized average convergence time to the absorbing state τ (d), and stationary density of active links in surviving runs ρ^{surv} . Averages are taken over 10^4 realizations of random regular networks where all nodes have $\mu = 4$ connections, whose number of nodes are $N = 250$ (circles), 1000 (squares), and 4000 (diamonds). In panels (f)–(i), characterization of the fragmentation transition in a nonlinear voter model with triadic closure in the rewiring events [603], for an Erdos–Renyi network with mean degree 8. The (p, q) -phase diagrams for the absolute value of the magnetization (f), for the normalized size of the largest connected component (g) and for the fraction of nodes belonging to isolated components in the fragmented state are shown. In (i), a sketch of the phase diagrams with a network realization corresponding to each phase. Panel (a) adapted from [602], panels (b)–(h) adapted from [604] and panel (i) adapted from [603].

An illustration of the phenomenology behind coevolving models is presented in Fig. 8. Agents hold a binary opinion $S_i = \{\pm 1\}$, and at each time step, a node i and one of her neighbors j are chosen. If both agents agree on the matter, $S_i = S_j$, nothing occurs. When they disagree, $S_i \neq S_j$, with probability $1 - p$, agent i adopts j 's opinion, thus $S_i = S_j$. But with probability p , i breaks her relationship with j and creates a new tie with a randomly chosen agent a such that she is not already connected to i and adopts her opinion, thus $S_i = S_a$. Clearly, p is the rewiring probability and is used as a control parameter. It turns out that there exist a critical value p_c separating various phases. When looking at the relative size of the largest network component S , it separates the region for which $S = 1$, for small rewiring, from the region in which $S/N \neq 1$, occurring at $p > p_c$. In the latter case, the network gets fragmented into two large components of size $S \lesssim N/2$ along with components whose size is much smaller than the number of agents N in the population. The magnetization $|m| = \sum_i S_i/N$ also brings information about the nature of the transition and the final configuration of the system. Indeed, in the single-connected regime $p \leq p_c$ all nodes share the same opinion, displaying full consensus $|m| = 1$. When the network fragments, the magnetization tends to $|m| = 0$, indicating that both opinions have a similar share of agents. Whether disconnected clusters are in local consensus or not is evaluated through the density of active links, which are the links that join nodes in different opinion. It is observed that the stationary density of active links in surviving runs of the dynamics, ρ^{surv} , reaches a finite steady value, which, however, decreases with the rewiring probability p within the region $p \leq p_c$. It vanishes continuously at $p = p_c$, indicating a second-order phase transition between the active and the frozen configurations. Put otherwise, in the final fragmented configuration, there exist consensus within the isolated groups. Regarding the average time τ to reach an absorbing state, we observe its divergence when $p \rightarrow p_c$, a signature of the critical slowing down of phase transitions.

For scenarios with discrete opinions, voter models [604,606] and multistate variants of it [605,607] have been largely employed as testbeds of opinion–topology coevolution. Yet, alternative social models with discrete node states have also been put forward [608,609]. In a similar fashion to the analyses in static networks, social influence mechanisms other than the voter model's copying one have been implemented into the models in order to understand their impact on the final configuration of the adaptive process. For instance, idiosyncratic opinion changes, modeled as noise, in the standard (linear) voter model [610] and a nonlinear variation [611]. Regarding the group influence in the agent's opinion change, the nonlinear voter has been extensively studied in this coevolving context [603,612,613]. Moreover, this family of models has also been approached from a more classical statistical physics perspective, with efforts directed towards unraveling conservation laws [614] and symmetry breakings [613].

Coevolutionary dynamics have also been explored in the context of continuous opinion models. The Deffuant–Weisbuch model discussed above has also been studied under different types of link rewiring. For random rewiring [615, 616], it is found that the convergence time to the steady state is determined by the characteristic time of link rearrangement. Achieving global consensus, on the other hand, is harder than in the baseline model because the rewiring makes it easier for large connected clusters to be broken in smaller parts. In fact, the number of finite-size clusters significantly decreases, as agents can more easily find others to agree with. A rewiring protocol that accounts for transitive homophily and neighbor effects has also been proposed [617,618]. It favors link reconnections towards agents that hold an average neighbor opinion that is closer to the opinion of the focal node that decided to rewire its link. When implemented, networks with a smaller degree assortativity, a smaller spectral gap, and fewer connected components than the baseline adaptive DW model are obtained. Other continuous opinion models have been explicitly laid down to be studied under the coevolving framework as well [619].

Liu et al. [620] explored a coevolutionary percolation model in which the network structure itself adapts dynamically based on user opinions and homophily. Their model coupled Deffuant opinion updates, where opinions converge if they fall within a certain tolerance, with a rewiring mechanism. Specifically, if the opinions of two connected users differ by more than a tolerance ϵ , they sever the tie with probability h and then reconnect to a like-minded node. Their mean-field analysis focused on the cross-opinion edge density ($\rho_{\times}$) and revealed a critical rewiring probability h_c , above which the network fragments into polarized echo chambers. Numerical simulations consistently validated these analytical predictions, producing scaling laws for fragmentation time, $T_{\text{frag}} \sim |h - h_c|^{-\alpha}$, with the exponent α being dependent on degree heterogeneity. This work compellingly demonstrates that even subtle changes in homophily-driven rewiring can dramatically impact polarization outcomes and, consequently, reshape information diffusion paths. This study effectively bridges opinion dynamics and network evolution, offering a dynamic perspective on how social structure is both shaped by and, in turn, influences the spread of ideas.

Kozitsin et al. [621] analyzed data from VKontakte, i.e. the most popular online social platform in Russia, to fit a mean-field kinetic opinion model that explicitly incorporates the effects of algorithmic recommendations, or filter bubbles. In their model, each user's propensity to interact with another is weighted by a similarity function $w_{ij} \propto e^{-|x_i - x_j|/\sigma}$, where σ reflects the platform's filtering strength. The kinetic equation governing opinion evolution yields polarized steady states for small values of σ . They found that the observed VKontakte polarization matched an empirical $\sigma_{\text{emp}} \approx 0.4$, suggesting that recommendation algorithms effectively lower the tolerance for opinion differences (ϵ_c), thereby accelerating the formation of echo chambers. This study is significant for bridging opinion dynamics, network science, and the real-world impact of algorithmic design on social polarization, offering a physics-inspired framework to understand how platform policies shape collective behavior and information exposure.

Coevolutionary dynamics with continuous opinions have not only been addressed in the context of pairwise interactions of the DW model, but also in the Hegselmann–Krause model; see, e.g., Ref. [622].

As a final remark, we note that coevolving adaptive models have been used to address socially-inspired phenomena other than opinion dynamics itself, such as role differentiation [623] and evolution of cooperation [624] in game theory, language dynamics through majority rules [625], cultural evolution [626], collective motion [624] and synchronization [627]. The so-called activity-driven time-varying networks framework has also been developed to integrate activation patterns of the agents with the network evolution, but it has been primarily explored in spreading (epidemiological, rumors) contexts and not so much in opinion dynamics [50,628,629].

Let us conclude by noticing that coevolutionary models show in a transparent way how homophily, rewiring, and social influence can jointly generate fragmentation and polarized macroscopic states. However, the empirical identification of the corresponding feedback mechanisms remains challenging, since real platforms combine endogenous tie adaptation, recommendation systems, exogenous shocks, and changing participation in ways that are difficult to disentangle from observational data alone.

6.6. Realistic features in the temporal interactions: memory effects, burstiness and non-Markovianity

In the last couple of decades, big data analyses have revealed that the temporal dimension of human activity patterns is fairly more complex than what traditional hypotheses supposed. This includes sociotechnical interactions that require both a direct and indirect interactions of people with other people or with technological devices, such as phone calls [630], writing emails [631], web browsing [632], or face-to-face encounters between school students [633], among others. On top of that, evidence from psychological experiments abounds regarding the fact that agents' opinions and beliefs are shaped by memory, e.g., in political voting [634], in the evaluation of pleasurable experiences [635] and pain [636,637]. Normally, the working assumption has been that the underlying statistics of opinion dynamics, when it comes to modeling them, are Poissonian and memoryless, i.e., the social activities are performed at a constant rate and independently of other previous activities [638–640]. As a matter of fact, both the mathematical approaches based on master, Langevin and Fokker–Planck equations, and the computational approaches based on standard Monte Carlo methods [641], the most widespread techniques to simulate statistical physics problems, present the aforementioned properties. Data finds systematic and significant deviations from this behavior; see Fig. 9 for an example of the interaction patterns between 4 different pairs of Twitter users. Since opinion dynamics relies on the interaction among agents, it is fundamental to know how to identify and measure these nontrivial temporal patterns and to unravel the mechanisms that originate them, with

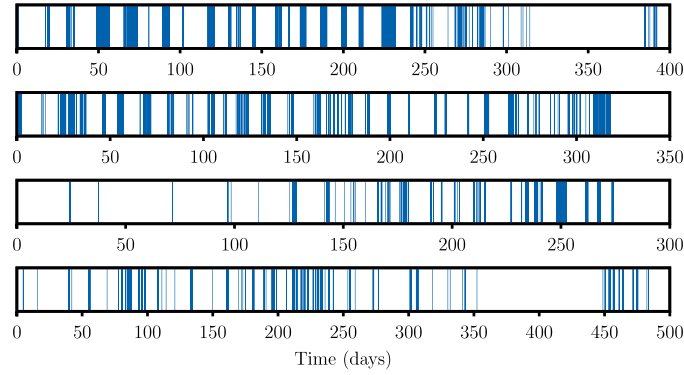


Fig. 9. Activity patterns between 4 different pairs of Twitter users. Every vertical line corresponds to a directed public interaction among them, so interevent times are the distance among two consecutive ticks. The measure of time is relative to each pair of users, thus, $t = 0$ corresponds to their first recorded interaction. In the figures are displayed 1914, 1198, 695 and 823 messages, respectively.

the ultimate goal of incorporating them into the opinion dynamics models to understand the qualitative and quantitative role they play. This is the pipeline that we follow in this section. A wealth of research has been devoted to these aspects; for recent reviews see [642,643].

Temporal activation patterns can be seen as time series $\{t_i\}$, $i = 0, 1, 2, \dots$, where t_i denotes the time at which an agent performs an activity that yields interactions with other agents. We disregard time series such that $\{(t_i, z_i)\}$, where z_i is a measure associated to the event i , because most works on heterogeneous temporal patterns in opinion dynamics are primarily interested in scenarios in which the events do not have duration (e.g., receiving an email) or their duration is much smaller than the total time window under consideration (e.g., a phone call against a lifelong kinship) so they can be approximated as a point in the time dimension. We stick to this convention here. Based on this, a quantity of paramount importance to characterize temporal patterns is the interevent time (IET), the time elapsed between two consecutive events $\tau_i = t_i - t_{i-1}$. $P(\tau)$ denotes the probability density function of $\{\tau_i\}$.

A common feature present in most human interactions is the so-called burstiness [644,645], i.e., periods of very intense activity within short time windows, the bursts, followed by long periods of inactivity; see Fig. 9 for examples of bursty time series. Generally, $P(\tau)$ is fat-tailed, and there is no dominance of a single timescale.

To quantify the amount of burstiness of a time series, Goh and Barabási have proposed the burstiness coefficient [646]

$$B = \frac{\sigma - \langle \tau \rangle}{\sigma + \langle \tau \rangle}, \quad (28)$$

where $\langle \tau \rangle$ and σ are the mean and variance of the $P(\tau)$. Clearly, $B \in [-1, 1]$. The extreme case $B = -1$ corresponds to a completely regular time series $P(\tau) = \delta(\tau - \langle \tau \rangle)$, while $B \rightarrow 1$ is approached for interevent time distributions with larger and larger variances, that is, very bursty signals. For a Poisson process, we have $B = 0$.

The interevent time distribution, and by extension, the burstiness coefficient, does not contain information about the order of the events. Therefore, these quantities are not suitable to obtain information about temporal correlations in social processes, i.e., how past events influence future ones. There are several proposals to quantify these correlations. One is the so-called memory coefficient [646]

$$M = \frac{1}{n-2} \sum_{i=1}^{n-2} \frac{(\tau_i - \langle \tau \rangle_1)(\tau_{i+1} - \langle \tau \rangle_2)}{\sigma_1 \sigma_2}, \quad (29)$$

where n indicates the number of events in the time series, $\langle \tau \rangle_1$ (resp. $\langle \tau \rangle_2$) and σ_1 (resp. σ_2) are the mean and the standard deviation of the set of values $\{\tau_i\}$ (resp. $\{\tau_{i+1}\}$), with $i = 1, \dots, n-2$. This is nothing else than the Pearson correlation coefficient for each pair of consecutive events. The memory coefficient ranges from -1 to 1 and the value $M = 0$ corresponds to an uncorrelated time series. $M > 0$ represents positively correlated activity patterns in which short (long) interevent times are followed by short (long) ones. For negative correlations, $M < 0$, the behavior is reversed: short (long) interevent times are followed by long (short) ones.

In a similar spirit, the so-called local variation parameter [647]

$$LV = \frac{3}{n-2} \sum_{i=0}^{n-2} \left(\frac{\tau_i - \tau_{i+1}}{\tau_i + \tau_{i+1}} \right)^2, \quad (30)$$

has been introduced in the context of neuroscience, which takes the values 0, 1 and 3 for regular, Poisson, and strongly bursty time series. The advantage of this measure over the memory coefficient is that it does not require the moments

of the time series but only the values of consecutive interevent times, so the correlation can be dynamically computed. Finally, one can compute the conditional probability $P(\tau|\tau')$, defined as the probability of observing an interevent time of value τ given the anterior one was τ' [648]. This is a quantitative measure but, at the same time, brings qualitative information. Indeed, by plotting $P(\tau|\tau')$, for example, as a heat map, one can know where the probability concentrates, and how the time series is positively or negatively correlated.

To measure correlations beyond consecutive events, we have the autocorrelation function [649]

$$A(t_d) = \frac{\langle x(t)x(t+t_d) \rangle_t - \langle x(t) \rangle_t^2}{\langle x(t)^2 \rangle_t - \langle x(t) \rangle_t^2}, \quad (31)$$

where t_d is the delay time, which sets the lag between two observations, and $\langle \cdot \rangle_t$ is the time average over the observation period. When there are correlations in the signal, it decays as a power law $A(t_d) \sim t_d^{-\gamma}$. The exponent γ can be related to other quantities, such as the exponent of the underlying fat-tailed interevent time distribution [650] or the Hurst exponent [651].

It may occur that the autocorrelation function decays as a power law if the time series is heterogeneous enough, yet with independent interevent times, as reported in [652]. This is an important point to remark, as sometimes it yields confusion: power-law interevent time distributions and power-law autocorrelation functions can be found even if the sequence of interevent times is uncorrelated. Aiming at finding a measure to correctly disentangle the correlations from the heterogeneity, [652] proposed the bursty train size distribution $P_{\Delta t}(E)$. It computes the number of consecutive events E that are separated from one another by a time window smaller than Δt . This distribution is exponentially distributed for uncorrelated sequences of interevent times. Hence, any deviation from an exponential $P_{\Delta t}(E)$ indicates event-event correlations.

Once burstiness and interevent correlations in human interacting patterns are reported, we need to unravel the mechanisms that make these properties emerge in order to later test their consequences in models of opinion dynamics. In the literature, we find several proposals that are apparently contradictory from one to another, hinting at the fact that there is not a universal mechanism responsible for the emergence of burstiness and correlations, and one must be careful when transferring the conclusions from one scenario to another.

One possible explanation for the power-law decay of the interevent time distribution is based on queuing theory [3]. Agents have a list of activities, each of which has a priority assigned. At each time step, the agent chooses between performing the highest priority task with probability p or performing a random task with the complementary probability. These probabilities can be justified by the finite cognitive capacities in the task handling of human beings. In this setting, the time a task spends in the queue follows a power law of exponent -1 , which reproduced the empirical findings in an email dataset. When human–human interactions are taken into account in the queuing model, interevent time distributions with a larger variety of exponents are found [653], better encompassing the wealth of decays observed in different datasets [642]. Other modifications in the particular rules of the model can induce other decay exponents that agree with other datasets [632,654,655]. Analytical treatments of queuing models have been put forward [656–658], as well as their study in nontrivial topologies [659].

Explanations of other nature consider coupled Poissonian models. [660] proposed a simple setting to obtain power-law interevent times by assuming a group of Poissonian agents with different characteristic timescales or a single nonstationary agent that change its rate. Other work in this direction is the one of [661], which assumes that when performing activities, there are two coupled types of processes acting at different timescales. The primary one is a non-homogeneous Poisson process with periodic time-dependent rate $\lambda(t) = \lambda(t+T)$, being T a period (the authors account for circadian and weekly patterns). The secondary process, that is performed when the primary one activates, is a homogeneous Poisson process that leads to a cascade of activity for a randomly selected number of events. The authors achieve an accurate reproduction of email activity patterns, and they conclude that the circadian and weekly cycles are key elements to describe the heavy tails in agents' communication. Some years after, however, it has been proposed [662] a method to de-season a time series, that is, to remove the effects of the daily and weekly cycles from the data, finding that the heavy tails remain robust after this procedure. In other words, the consideration of circadian and weekly rhythms in a model can induce broad interevent time distributions and possibly has an impact on real task execution patterns, but these cycles may not be the fundamental reason for the observation of long tails in the distributions.

Although the phenomenon of broad interevent time distributions has been extensively studied and models of diverse nature have been proposed to reproduce them, the discussion on how to generate temporal series with interevent correlations to be incorporated in the opinion dynamics models has been much more scarce. On the one hand, some numerical algorithms to generate correlated time series with underlying power-law interevent distributions are known, such as [663–665]. On the other hand, an option for mechanistic models to generate the desired correlations is to endow the system with some sort of memory. For instance, in [652] an agent is assumed to be in two possible states, the normal and the excited one, and there are transitions between these states. In the former, events are executed independently, while the events performed in the latter correspond to the bursts. The probability of exciting the system is constant, but the de-excitation probability depends on the number of consecutive events in the excited state. Besides, the probability of performing the next event also depends on the time elapsed since the last event.

Models that endow agents with memory can also generate fat-tailed interevent time distributions in a bottom-up manner. This has been achieved through what has been dubbed aging. The age of an agent τ is not to be confused with

her physical age, but it is taken as the time since the last change of her state/opinion. Aging is then implemented such that the probability of execution of an event (e.g. an interaction with a neighboring agent in order to adopt her opinion) is modified in accordance with an age-dependent probability $P_a(\tau)$. This kind of long-term memory in the nodes and also in the links has been used to explain the emergence of heterogeneous activity observed in large-scale communication networks [666].

To mimic the positive correlations observed in data, this probability must be a decaying function of the age, i.e., the longer an interaction has not taken place, the more difficult it is to do so. However, different choices of $P_a(\tau)$ will modify in a different manner the dynamics of the model on which aging is considered. For example, in the case of the voter model, it has been found that the formation of consensus can be accelerated by selecting a linear probability in the age [667] or by including latency periods after opinion changes of the agents [668]. In the latter case, the voter model can also experience oscillatory behavior [669]. Fernández-Gracia and coauthors have shown that a decaying $P_a(\tau) \sim \tau^{-1}$ not only yields power-law interevent time distributions between opinion changes but also drives the voter model to consensus through a coarsening process even if simulated in the regime $d > 2$ [670]. In low-dimensional lattices, the coarsening properties of the voter model have also been modified through memory effects [671]. Hence, the inclusion of memory in the actions of the agents leads to phenomena that are radically different from those observed for the memory-less cases. This has been further verified by including aging in other models of opinion dynamics, such as in the noisy voter model [672]. In there, it has been shown that aging is able to change the universality class of the dynamical model, and make the pseudo-critical size-dependent critical point of the modality transition becomes independent of N . This type of aging has been generalized and its consequences investigated recently, within the family of voter models [673–675] and other models relevant to sociophysics, such as the Schelling model [676], threshold models [677], and the majority rule model [678], among others. For the q -voter model, a time- and memory-dependent noise has also been implemented, motivated by the fact that agents may possess their own memories of past experiences related to the social costs and benefits of being independent (noisy updates) or conformist (group influence) [679].

Moreover, we underscore that including aging not only offers new dynamical behaviors, which is interesting from a fundamental point of view, but also is capable of reproducing real-world features, such as global oscillations of the global dynamics in the voter model [680] and in the spatial prisoner's dilemma game [681,682].

Another aspect that has been largely explored under the lens of heterogeneous interaction patterns is the time it takes for a system to reach consensus. It has been found that consensus can be delayed with respect to the memoryless case [683], but the interaction network plays a crucial role in determining the final amount. However, when burstiness and temporal correlations are intertwined with topological correlations, in the form of communities, it has been reported that the time to consensus may speed up or slow down with respect to the uncorrelated case, depending on the intensity of each correlation [648]. Similar results regarding the speed-up/slow-down due to the interplay between topology and temporal correlations are found in continuous-opinion bounded confidence models such as the Deffuant–Weisbuch and the Hegselmann–Krause discussed above [684,685] and diffusive processes [686]; see also [60,687]. For spreading models, it has been shown that prevalence decay times under long-tailed interevent time statistics make prevalence decay times considerably larger than what is predicted by the standard Poisson process-based models [688] and that the large heterogeneity found in the response time is responsible for the slow dynamics of information at the collective level [689]. This is robust for other types of temporal correlations [690].

7. Summary and conclusions

The advent of the Internet and social media has fundamentally reshaped the information landscape, blurring the boundaries between physical and social networks and creating a dynamic, complex adaptive information ecosystem. This landscape, where news, rumors, and opinions spread at unprecedented speed and scale, is rife with unreliable and competing content, making rigorous scientific analysis essential. The inherent complexity of these socio-technological systems—characterized by disordered connectivity patterns, nonlinear dynamics, and active, adaptive agents—poses significant challenges for traditional analytical approaches. This review has argued that statistical physics and network science provide a valuable quantitative framework for clarifying many of the mechanisms governing these systems, complementing descriptive and data-driven approaches.

The study of collective social dynamics necessitates first characterizing the medium. We have shown how the analysis of social media platforms (particularly X, Facebook, and Reddit) reveals distinct topological and algorithmic features that shape information diffusion. Network models, including random graphs, preferential attachment frameworks, and fitness-based approaches, have proven essential in quantifying how information disorders emerge from platform architectures. Maximum entropy null models, in particular, provide a robust baseline for distinguishing organic information flow from artificially amplified campaigns. At the mesoscopic scale, structural features like echo chambers and polarized communities arise naturally from homophilic interactions and algorithmic reinforcement. At the macroscopic level, abrupt changes in visibility, reach, or collective attention can in some cases be usefully interpreted through the lens of threshold phenomena and phase-transition-like behavior, although the empirical evidence for sharp critical behavior remains context dependent. The properties of these networks—being directed, weighted, and signed—encode how information flows and provide critical insights into the macroscopic spread and microscopic user dynamics.

The core of the review addressed how and how fast news, rumors, and opinions spread, showing that the dynamics of propagation are governed by both simple and complex contagion processes. While some false narratives spread

through viral, broadcast-like mechanisms (simple contagion), others require repeated exposure or social reinforcement (complex contagion), particularly in ideologically insulated communities. Threshold models and bounded-confidence opinion dynamics help clarify how reinforcement, selective exposure, and network coevolution can sustain polarization and make certain beliefs—including false or misleading ones—more resilient over time. The temporal dimension adds further complexity, including phenomena such as burstiness, memory effects, and non-Markovian interactions. This requires temporally resolved models that capture the non-stationary dynamics of these ecosystems, reinforcing the need to investigate the principles at the basis of spreading patterns in disordered structures, as well as measuring the pervasiveness of different narratives in online media.

We examined the conditions under which a population may reach consensus, polarization, or fragmentation by reviewing discrete opinion models, like the Voter model and its variations, and continuous models, such as Deffuant–Weisbuch and Hegselmann–Krause. These frameworks reveal that even minor perturbations in network structure or information exposure can trigger large-scale shifts in collective belief systems. Human factors, including confirmation bias, motivated reasoning, and identity-protective cognition, play a critical role, as social psychological research underscores how these biases amplify susceptibility to false narratives. The interplay between individual decision-making and social dilemmas—such as the trade-off between sharing speed and accuracy—further complicates mitigation efforts, highlighting the necessity of bridging micro-level cognitive biases with macro-level societal divides through mesoscopic analysis.

The focused study of information disorder (misinformation, disinformation, and mal-information) represents a critical and timely application of this physics-based framework. Here, key structural and dynamical insights have been leveraged to examine the mechanisms through which false narratives propagate, persist, and evolve. Efforts to combat disinformation must account for the adaptive nature of both malicious actors and platform ecosystems. Source detection methods, including network-based attribution and machine learning classifiers, face persistent challenges from obfuscation tactics, such as sockpuppet networks and cross-platform hopping. Meanwhile, content moderation policies often struggle to balance censorship risks with the need for rapid intervention, particularly in encrypted or private spaces where disinformation thrives. At the same time, the empirical calibration of these models remains difficult, as it depends on operational definitions of misinformation, platform-specific visibility mechanisms, and heterogeneous cognitive responses to corrections and interventions.

This leads to the practical question of whether we can design effective, physics-informed interventions to mitigate misinformation diffusion. Innovative approaches—such as probabilistic fact-checking, network inoculation strategies, and decentralized reputation systems—show promise but require scalable implementation. The integration of behavioral nudges (e.g., accuracy prompts) with structural interventions (e.g., algorithmic transparency) may offer a multi-layered defense. However, the rapid evolution of generative AI and synthetic media demands continuous adaptation of detection and response frameworks.

Ultimately, the physics of news, rumors, and opinions has emerged as a valuable unifying perspective, showing that these phenomena are not merely social or technological issues, but also complex adaptive systems shaped by general principles of collective dynamics, stochastic processes, and network organization. Future research should prioritize cross-platform analyses to track information migration and resilience, and develop policy-relevant simulations to stress-test interventions under realistic, dynamic conditions. By grounding these efforts in empirical network science and theoretical advances in stochastic processes, phase transitions, and percolation theory, while respecting the complexities of human behavior, we can better navigate the challenges of our hyperconnected information age and contribute to a more informed and resilient digital society.

CRediT authorship contribution statement

Guido Caldarelli: Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization. **Oriol Artime:** Writing – review & editing, Writing – original draft, Methodology, Investigation. **Giulia Fischetti:** Writing – original draft, Methodology, Investigation. **Stefano Guarino:** Writing – review & editing, Writing – original draft, Methodology, Investigation. **Andrzej Nowak:** Writing – original draft, Methodology, Investigation. **Fabio Saracco:** Writing – review & editing, Writing – original draft, Methodology, Investigation. **Petter Holme:** Writing – review & editing, Writing – original draft, Methodology, Investigation. **Manlio De Domenico:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Guido Caldarelli reports financial support was provided by European Commission. Oriol Artime reports financial support was provided by Spanish Government. Andrzej Nowak reports financial support was provided by European Commission. Oriol Artime reports financial support was provided by Government of Catalonia. Stefano Guarino reports financial support was provided by Ministero Università e Ricerca, Italia. Fabio Saracco reports financial support was provided by Ministero Università e Ricerca, Italia. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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