Network science for social communication studies

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June 7, 2025

Abstract The rise of digital platforms has reshaped social communication, introducing new complexities that require novel analytical approaches. Despite the increased attention to the study of online communication, researchers have yet to adopt a unified methodology for studying this phenomenon. This chapter examines the state of the art of network-based approaches to study communication from a computational perspective. In particular, it presents a flexible framework for studying social (online) communication within the context in which it occurs and for addressing the challenges posed by its multifaceted nature. In this work we: (i) identify the five ingredients for modeling communication with networks (actors, content, links, time, and context); (ii) review network-based methods and models, and provide metrics to measure conversational aspects of communication; (iii) categorize current research objectives and applications. Our goal is to provide a structured overview of the field, encouraging further exploration of how network science can enhance the study of communication in an increasingly complex and dynamic environment.

Keywords social communication, online communication, network science, networks

1 Introduction

The ubiquity and accessibility of online media have fundamentally transformed social communication, promoting new types of interactions that are faster, involve more participants, and are considerably more persistent than traditional communication (boyd 2010; Locher 2015; Magnani et al. 2012). Social communication today manifests in various forms, from direct messaging to thread-based exchanges on social media platforms. While the fundamental principle of social communication — the exchange of information between actors — remains the same, the study of *online* communication introduces new unique computational challenges (Bolander and Locher 2020). These challenges arise from the multifaceted nature of the communication act, such as hidden intents (the purpose of participants), invisible audiences (intended recipients of the message; Hanteer et al. 2018a), and the proliferation of platforms and virtual environments where the communication occurs. The mixed use of different modalities, such as text, emojis, images, audio, and videos, further complicates the analysis (Locher 2014). In response, researchers have developed new approaches for studying social communication, particularly in digital contexts where interactions are increasingly mediated. Network science has emerged as a powerful framework in this domain, providing tools to analyze and model complex communication dynamics (S. Borgatti et al. 2018).

In this work, we examine current approaches for studying social communication through a network-based perspective. Research efforts have sought to structure the complex and evolving landscape of online communication by developing theories and frameworks to organize and interpret new dynamics, aiming at bringing clarity to the otherwise chaotic and fragmented nature of digital interactions. However, structuring and organizing this field is an inherently complex, gradual, and heterogeneous process. Theories, models, and applications evolve unevenly as researchers focus on different aspects of communication depending on their disciplinary backgrounds and methodological approaches (Peel et al. 2022). Despite significant progress, the field remains highly adaptive to emerging challenges and continues to evolve in unpredictable and divergent directions. Simultaneously, the digital communication landscape is advancing rapidly, driven by technological innovations, and expanding across disciplines.

Network-based methods have proven particularly effective in addressing foundational research questions in the social sciences, especially concerning communication (S. Choi 2020; Hilbert et al. 2019). These methods have had a significant impact, offering analytical possibilities such as modeling the structure of digitally mediated communication, where networks represent user interactions (Goglia and Vega 2024), or the diffusion of sentiment and ideas (Butts et al. 2023). Networks provide an intuitive and flexible approach to represent and analyze the structure of social connections, interactions, and relationships, making them essential for studying complex systems. Network-based methods have been applied across multiple disciplines to understand organizational linguistic patterns (H. Chen 2023; Grobelny and Michalski 2022; Raviv et al. 2020), track communication pathways in healthcare (Francis et al. 2024; Saatchi et al. 2023), analyze emergency response coordination (Kapucu et al. 2023), and examine the spread of misinformation in political and health campaigns (Spiro 2020; Unlu et al. 2024). However, applying these methods to online communication introduces unique challenges, such as managing vast and heterogeneous datasets, accurately modeling user behavior, and accounting for the dynamic and rapidly evolving nature of digital platforms (Van Atteveldt and T.-Q. Peng 2018).

In this chapter, we discuss how recent advances in network science open new avenues for addressing the complexity of digitally mediated communication. We begin by examining how social communication has evolved into an increasingly complex phenomenon that can be effectively modeled and analyzed using networks (Section 2). Next, we identify the ingredients for modeling social communication with networks (Section 3). We then review network-based metrics, methods, and models commonly used in diverse applications (Section 4). We conclude by categorizing current applications into research areas, drawing on real-world examples (Section 5). Through this exploration, we aim to (i) synthesize and organize existing network-based tools and approaches, (ii) stimulate further discussions on how they can be refined and applied to analyze communication in digital environments, and (iii) advance ongoing efforts to critically examine how network science contributes to understanding and modeling social systems and phenomena.

2 The complexity of contemporary communication

Communication plays a fundamental role in our lives, enabling us to understand the world and shape our identities. Beyond mere information transmission, it involves an interactive dimension centered on building and maintaining social relationships (Tanskanen et al. 2024). In this dynamic process, the contributions of senders and receivers extend beyond simple message exchange: they navigate social roles, power dynamics, and shared meanings, with both parties actively shaping the interaction (Cobley and Schulz 2013). Cultural, social, and psychological factors further influence how messages are constructed, interpreted, and responded to, revealing communication as a multifaceted and intricate phenomenon. Communication serves multiple purposes, from reinforcing social norms to fostering social bonds. The diversity of actors, content, goals, and interaction contexts all play a significant role in shaping how and why messages are formulated and interpreted. Modern technologies and media add layers of complexity to this already intricate landscape. Historically, mass communication was regarded as a tool for societal progress, enhancing the flow of information. However, access to information was limited, and significant barriers to expression existed. With the advent of the Internet, social media platforms, and other digital tools, new dynamics have emerged, increasing the speed and volume of communication while introducing new modalities such as asynchronous conversations, multimedia content, and anonymous interactions that were absent in traditional face-to-face exchanges. Consequently, contemporary communication transcends physical proximity and time constraints, giving rise to new behavioral patterns. Conversations are now *persistent*, meaning they can be accessed later, searched, replayed, visualized, and restructured (boyd 2010; Locher 2015; Magnani et al. 2012).

Today, the ability to engage in communication extends beyond humans to include artificial agents, such as bots and virtual assistants, which simulate human-like interactions. Chatbots, particularly those powered by large language models, have emerged both as new participants in conversations and as mediators shaping human communication (Hepp et al. 2023). Another example of AI-mediated communication is the integration of generated suggestions and responses in email applications: while interactions remain fundamentally between humans, AI interventions actively contribute to the communication process. This interplay between human agency and AI assistance highlights the evolving nature of communication in the digital age and raises important questions about the role of artificial agents in shaping interactions, as well as their implications for authenticity. As these technologies evolve, they challenge the traditional understanding of communication and invite further exploration into human-machine interactions, including issues of trust and the potential for miscommunication.

Given this intricate landscape, communication requires a deeper analysis and robust, versatile models capable of capturing its diverse aspects. As noted previously, network science has emerged as a powerful framework for analyzing the structure and evolution of complex phenomena such as social communication in the digital era. Communication is indeed increasingly conceptualized as a complex system composed of dynamic and interacting elements (S. P. Borgatti et al. 2009; Helbing et al. 2015). A key advantage of applying a network perspective to social science problems is its emphasis on *relationships*. Network science focuses on social entities and individuals "in interaction with one another" and examines how they constitute a "structure that can be studied in its own right" (Wasserman and Galaskiewicz 1994). For example, in social and cultural anthropology, researchers have used network analysis to map and quantify social ties that sustain cultural practices and facilitate knowledge transmission through communication (*Wayback Machine* 2021; Wolfe 2011). Similarly, in political science, relational concepts have enabled the exploration of interactions among individuals and institutions, shedding light on the origins and outcomes of collective actions (Maoz 2017). By integrating qualitative studies on language and social interactions with quantitative insights from network analysis, scholars are developing a more comprehensive understanding of social communication.

This chapter primarily focuses on recent network-based developments, examples, and applications to illustrate the current state of human-like communication. However, the analysis is not confined to digital contexts, since offline social communication remains highly relevant. By applying network-based approaches, scholars can study both online and offline social communication in novel ways, providing fresh insights into long-standing social patterns, such as those found in communities, workplaces, and familial structures.

3 Five ingredients to model social communication

This section outlines five core elements of communication analysis, based on the literature reviewed in this chapter. We identify these elements as the *ingredients* of social communication, which serve as essential components for modeling communication with networks: actors, content, links, time, and context.

1. **Actors.** The first ingredient, *actors*, refers to *who* is involved in the communication, often encompassing people. Nevertheless, limiting the scope to individual human agency provides an incomplete picture of social communication (Contractor et al. 2011; Waldherr et al. 2019). Actors, usually included in networks as nodes, can embody a variety of communicative entities, such as automated accounts (bots), artificial agents, organizational profiles, collectives, or abstract concepts. In this regard, it is worth considering Actor-Network Theory (ANT) as an effective conceptual framework to model and study social communication from a comprehensive perspective, as it incorporates nonhuman actors and non-individual entities (Contractor et al. 2011).

   Actors can be either active or passive participants: active actors engage directly in communication, while passive actors, like "lurkers", observe discussions without contributing but still experiencing the communication effects, therefore being involved in network dynamics (Perna et al. 2018; Saxena and Reddy 2021). Additionally, some actors may function as proxies, representing individuals or groups through intermediaries (e.g., public figures communicating through managed media accounts; Y. Chen et al. 2024; Ruths and Pfeffer 2014), introducing complexity around direct versus mediated communication. In online contexts, multi-account use further diversifies actor representation, as individuals may maintain multiple profiles embodying distinct personas across or within platforms. Furthermore, consumers (i.e., information recipients; see Vega and Magnani 2018) are often hidden (Hanteer et al. 2018a), adding ambiguity and complexity to the representation of both the intended and potential audience.

   In network science, actors' characteristics are encoded as attributes — properties associated with each node, such as demographic features and behavioral patterns. This integration significantly extends modeling possibilities. Considering, for instance, Berlo's model of communication (Cobley and Schulz 2013), complex features like attitudes, beliefs, communication skills, and social and cultural contexts of actors can be expressed as node attributes, allowing for a richer representation.

2. **Content.** The second ingredient, *content*, represents *what* is communicated — the substance of a message. In communication networks, nodes can represent either the entire content — as in networks of tweets (Hanteer et al. 2018b; Martirano et al. 2023; Münch and L. Rossi 2020), emails (Barbucha and Szyman 2021; Fronzetti Colladon and Gloor 2019), and phone calls (Park et al. 2018) — or information extracted or inferred from it — such as topics (Belkaroui et al. 2015), sentiment, locations, events, and lexical items (Shadrova 2022). The latter can also be integrated as node attributes. Alternatively, in communication networks where links between actors indicate exchanges and interactions (see *Links* below), content can be included as edge attribute.

While textual content is commonly included in networks, communication nowadays extends beyond text to encompass images, videos, and audio, which significantly impact engagement dynamics (Bolander and Locher 2014). Xie, Natsev, et al. (2011) model a video graph with nodes representing YouTube videos and edges connecting nodes that contain the same meme. Expanding content analysis to include multimedia offers a holistic view of social communication. Recent advances in multimedia network analysis are helping bridge this gap, with new methods emerging to incorporate visual content into graphs (Arminio et al. 2024). The integration of non-textual content in networks currently remains a considerable challenge, as content often includes non-linguistic information that is difficult to represent. For instance, semiotic parts of the content like facial expressions, tone of voice, and body language, can be modeled as node attributes, improving the analysis of both offline and virtual face-to-face communication networks.

3. **Links.** The third ingredient, *links*, represents relations, interactions, connections, or associations between other ingredients. In network science, they are operationalized as edges, which frequently occur as actor-actor links that can describe information exchange, embodiment, influence, contact, and social relationships. For example, Aswath et al. (2020) model discussions as a social graph where nodes are communities (subreddits), and edges represent the presence and strength of conflicts between them. Content-content edges are also common for associations like linguistic similarity (Waldherr et al. 2019), co-occurrence (H. Chen 2023; Fudolig et al. 2022; Galluccio et al. 2022; Shadrova 2022), or reference (Jung and Segev 2022; Spitz and Gertz 2018). Actor-content edges — to represent generation, sharing, or consumption (Vega and Magnani 2018) — appear less frequently despite being a straightforward and effective choice to model communication links, typically defined as the "contact created by the flow of messages" among actors (Oh and Monge 2016).

   Links can vary in strength, directionality, and type. Edges can be assigned a *weight* to capture the intensity, frequency, or importance of communication exchanges. Word co-occurrence, for instance, is often modeled with edges representing the number of messages in which connected words appear together (Fudolig et al. 2022; Galluccio et al. 2022). *Directed* edges model unidirectional links (useful for asynchronous communication), while *undirected* edges model mutual links, allowing, for instance, a transactional approach to communication analysis (Cobley and Schulz 2013) with the representation of reciprocity and feedback. Communication networks that include multiple types of links are represented with specific models, such as multilayer networks (see Section 4.3).

4. **Time.** The fourth ingredient is *time*. It addresses the *when* dimension of social communication, which, as highlighted in Section 2, is an inherently dynamic process. Many real-world networks include connections that form, dissolve, and recur over time. These are known as temporal or dynamic networks. Examples include mobile communication networks, where a connection exists only for the duration of a call, or discussions in online platforms where actors join and leave conversations. Temporal networks have a well-established foundation in research (Holme and Saramäki 2012), with many studies examining the growing topology of communication networks (Goglia and Vega 2024).

   Time can be measured in multiple ways (see Section 4.1) and enhances the versatility of models, allowing the representation of message exchanges with a transactional communication approach (Cobley and Schulz 2013) and the analysis of content evolution, actors' interaction dynamics, or both (Vega and Magnani 2018). Time is usually embedded in networks at the edge level, where time stamps serve as link attributes (see *Links* above). These timestamps are present as metadata or extracted from the content; they can be expressed by a generic set of ordered annotations that denote absolute or relative time (ibid.). In multilayer networks (Section 4.3), the temporal dimension is typically modeled with separate layers that correspond to specific time intervals or phases of interaction (Tardelli et al. 2024).

5. **Context.** The fifth ingredient, *context*, addresses the *where* and *why* dimensions of social communication. Context provides the situational backdrop in which interactions occur, encompassing environmental factors and conditions that shape communication. Integrating context allows network models to capture often-overlooked aspects of social communication, such as platforms, environment, genres, and cultural settings. For instance, the channel (direct or mediated) and the medium (digital or physical) are part of the context since they include features that shape communication, as conceptualized in Berlo's and Schramm's models (Kubota 2019).

   Context enriches our understanding of motivations and influences underlying communication, including geographical, societal, and situational factors that affect message conveyance and interpretation. Incorporating context into networks is therefore crucial to allow a more comprehensive representation of social communication. However, it remains a significant research challenge, as there are no specific models or methods in network science to effectively accomplish this. Attempts have been made using multilayer networks (see Section 4.3), though they have yet to yield a comprehensive solution. At present, there is no established framework to guide this process. Therefore, research efforts aimed at developing approaches and techniques in this direction are essential.

These five ingredients provide a foundational framework for modeling social communication with networks. They offer a conceptual toolkit to help scholars expand beyond traditional modeling choices to account for the richness of social communication. In the following section, these ingredients will serve as a basis for exploring network metrics, methods, and models widely used in studying social communication.

4 Metrics, methods, and models

In this section, we review network science metrics (Section 4.1), methods (Section 4.2), and models (Section 4.3) commonly used for the study of social communication. We provide examples of usage referring to existing applications, which will then be organized into research areas in Section 5. Each metric, method, and model targets one or more communication ingredients described in the previous section.

4.1 Metrics

We organize the discussion by reviewing metrics first for network connectivity and then for node-oriented network analysis.

4.1.1 Social contact and influence

The essence of communication lies in intra- and inter- connections between actors and content (Section 3). As described in Section 2, the primary benefit of adopting a network perspective in social science research is its focus on relationships, which are represented by edges. Analyzing edges' quantity, strength, directionality, and structure reveals fundamental insights about the underlying mechanism of interactions. Distance metrics, such as *path length*, help analyze the information flow through both local and global connections, while *bridges* and *structural holes* help identify actors that connect disparate groups in a network, facilitating social contact (S. P. Borgatti et al. 2009). In communication studies, such metrics are useful to understand how content propagates in networks. D. Choi et al. (2015) assessed the virality of comments in networks of Reddit threads by computing the sum of shortest path lengths between all pairs of nodes (i.e., the Wiener Index).

Metrics for interconnectedness provide insights about how tightly knit networks are. *Density* indicates the probability for a random node pair to be connected and is measured as the ratio between the number of edges in a network and the total number of possible edges that can exist (Coscia 2021). In a highly dense communication network, such as a group of actors who frequently interact by replying, reposting, or mentioning each other, content spreads rapidly because of the multiple paths between nodes. Conversely, when density is low (i.e., in sparse networks) the information propagation may slow down and rely mostly on bridge nodes that ensure the connectivity. *Clustering coefficient* captures the level of transitivity in connections. It can be measured both at macro-scale, by counting the number of triads in a network that are closed by a triangle, or at meso-scale, by counting the number of triangles to which a given node belongs over the number of triads centered on it. Communication networks with a high clustering coefficient reveal, for example, the tendency of actors to form tightly-knit groups. All these cohesion measures quantify node connections within a network, being particularly useful, for example, in the study of coordinated behavior (Nwala et al. 2023; Pacheco et al. 2021), interactional organization (Brambilla et al. 2022) and diverse modes of social communication (Goglia and Vega 2024), as discussed in Section 5. Scholars found that communication networks with high density and high clustering coefficient might foster the formation of echo chambers, where actors reinforce their prior beliefs, resulting in polarized opinions (Banisch and Olbrich 2019).

Reciprocity is used to measure mutual connections between nodes in a network. In many communication models, interactions are bidirectional and involve feedback (Cobley and Schulz 2013), indicating balanced or imbalanced exchanges. Various reciprocity measures exist, including intra-reciprocity and inter-reciprocity, which assess reciprocal ties within groups and between different groups, respectively (Aiello 2015). Such metrics are useful in communication analysis for studying turn-taking (Cannon and Robinson 2023), group cohesion (Aiello 2015), and online communities growth (Tsugawa and Niida 2021).

Some metrics for communication networks' connectivity are defined to specifically capture time-related quantities, such as actors' activity levels and content engagement. *Contact time* marks when the interaction initiates, *duration* indicates how long an interaction is (Belkaroui et al. 2015; Holme and Saramäki 2012; Magnani et al. 2012), *frequency* represents how often interactions occur over time, while *latency* corresponds to the shortest path between two nodes in a temporal network (Holme and Saramäki 2012). Such measures are easy to compute, yet powerful to infer valuable insights about communication dynamics, such as the fact that "lies spread faster than the truth" in online news spread on Twitter (Vosoughi et al. 2018). For example, users' level of *rensponsiveness* (i.e., how fast conversation participants react) has been used to categorize Reddit threads (D. Choi et al. 2015). More complex measures can be derived from them, such as *conversa-*

tion density (Magnani et al. 2012), defined as the sum of interactions' (i.e., edges with timestamp attributes) frequency.

4.1.2 Node similarity and ranking

In Section 3 we discussed actors and content, indicating their traditional representation at node-level in networks. "At the node-level of analysis, the most widely studied concept is *centrality*" (S. P. Borgatti et al. 2009), a family of properties related to the structural importance of a node in networks. The problem of determining nodes' importance within a network is known as node ranking, which aims to assign a numerical value, or rank, to each node based on its position and connections within the network. Centrality-based measures have been widely utilized to assess actors' and contents' importance (Erkan and Radev 2011; Himelboim and Golan 2019; S. Kumar et al. 2024; X. Li, Zhou, et al. 2019; X. Li, Y. Liu, et al. 2016; S. Liu, Zhang, et al. 2023; Şimşek and Meyerhenke 2020; X.-H. Yang et al. 2021), also for temporal communication networks (Srour et al. 2022) to predict the evolution of such importance over time. Several centrality metrics have been developed[1] to assess how close a node is to others (*closeness*), how often a node acts as a bridge between other nodes (*betweenness*), how much a node is connected to influential nodes (*eigenvector*), and nodes position in densely connected substructures (*k-core*). By simply counting connections, the *degree* of a node measures how many edges it has. Intuitively, more edges increase the node's importance; highly connected actors send and receive more information, while highly connected content has more engagement or relevance. In directed networks, *in-degree* and *out-degree* measure the number of incoming and outgoing edges respectively, helping distinguish communication consumers from producers (Vega and Magnani 2018). Magnani et al. (2012) utilized in-degree to measure both users' and conversations' popularity. In the same work, an alternative measure of relevance for conversation networks has been defined based on content, as the sum of all messages' relevance (measured as text distance) over the number of interactions in the conversation.

In order to quantify similarity at node level, different metrics have been used, for example by comparing textual or visual content (edit distance, vector representation, cosine similarity of extracted features, etc.), or mapping it to other domains (e.g., sentiments or topics; Vega and Magnani 2023). Specifically, for social and communication networks, the concept of *homophily* implies that nodes establish edges among themselves if they have similar attributes. This comes from an intuitive concept in sociology which is that actors tend to associate with others having similar characteristics. In network science, homophily has been operationalized through measures of *assortativity*, which captures how much homophily drives networks' connections by measuring the probability of edges between actors (or contents) based on their attributes. In a perfect assortativity scenario (i.e., value 1) nodes are exclusively linked to others with identical attributes. Conversely, in a completely disassortative network (i.e., value -1), nodes only connect to others with different attributes, resulting in a structure where heterophily drives all relations and interactions. For example, in online social platforms, high assortativity by political affiliation can result in polarized groups where users are exposed only to viewpoints that reinforce their existing beliefs. This metric has been utilized in a wide range of applications, especially related to communication activities and effects (see Section 5), such as analyzing political polarization (Y. Chen et al. 2024; Hohmann et al. 2023), estimating social capital (Foucault Welles and González-Bailón 2020), studying echo chambers (Cinelli et al. 2021; Cota et al. 2019; Williams et al. 2015) and modeling the emergence of extreme ideas (Sayama 2020).

[1] See the periodic table of network centrality: http://schochastics.net/sna/periodic.html

4.2 Methods

Similarly to Section 4.1, we organize the discussion by first describing models for network connectivity and then for node-oriented network analysis.

4.2.1 Social contact and influence

Continuing the discussion around the study of connectivity, several network science methods have been proposed. The analysis of links has often been addressed with *tie strength* estimation, which measures contact intensity or closeness between nodes (Perikos and Michael 2022; Singh, Srivastava, et al. 2023). By examining tie strength in social communication studies, researchers can identify patterns of social cohesion and message diffusion. For example, related to the study of different modes (see Section 5), Iñiguez et al. (2023) analyzed tie strength in communication networks from 16 different channels, demonstrating that (i) people tend to build similar-looking personal networks on multiple online communication channels, and that (ii) relationships structure that exist in the offline world is reflected in online communication.

The study of communication spread in social networks has often been addressed using *percolation* (Hu et al. 2018; M. Li, R.-R. Liu, et al. 2021), which analyzes how network structure is affected by random node or edge removal/addition. In real-world communication networks, this can represent or simulate actors leaving/joining a conversation, the inaccessibility/availability of content, or the interruption/augmentation of communication channels and paths. A similar goal, which consists of predicting where potential new or missing connections might form in communication networks, is addressed by *link prediction* algorithms. Such algorithms, often utilized to enhance information diffusion or maximize outreach, exist both for static and temporal networks (Coscia and Szell 2021; A. Kumar et al. 2020; Singh, Srivastava, et al. 2023). Static link prediction algorithms use topological or structural network features, while dynamic link prediction algorithms fetch temporal information in addition to structural features during the prediction process (Singh, Srivastava, et al. 2023).

Another method for investigating connectivity patterns is *motif analysis*. Motifs are substructures that constitute "the building blocks of complex networks" (Coscia 2021), consisting of recurring patterns with a given topology (for example, a triangle is a motif). In social communication studies, motifs reveal fundamental interactions that govern how actors and content connect, like triadic closure, where mutual connections form between three nodes, fostering cohesion (Z. Li et al. 2024). They may also indicate hierarchical or feedback relationships, shedding light on power dynamics or information loops within a network. Identifying and counting relevant motifs in network is a hard problem, and scholars have proposed diverse algorithms for this purpose (Y. Fu and Huang 2024; J. Li et al. 2024). Motif analysis has been used to analyze scientific mobility and collaborations in co-authorship networks (Boekhout et al. 2021; Zou et al. 2023), and discover clusters of sightseeing spots in tourists' networks (Shao et al. 2021). The investigation of network motifs is often extended to encompass models like dynamic networks (see *Time* in Section 3), with time-evolving motifs.

The study of connectivity patterns lays the foundation for the investigation of information dissemination processes. The content of communication flows along network paths from one node to the other, generating phenomena like the contagion of ideas and the spreading of opinions (Chalakudi et al. 2023). When a message is sent, it may trigger a chain reaction (known as a *cascade*) where one individual's behaviors (like opinion adoption) lead others in their network to do the same. This cascading behavior often reflects the social influence mechanism in which individuals' decisions are shaped by the social actions and interactions of their peers. For example, studies have discovered relations between actors' social capital and their influence capacity (Chalakudi et al. 2023). The influence propagation of an actor or content is computed based on this cascade process with specific models for investigating information dissemination processes (see Section 4.3).

4.2.2 Node similarity and ranking

The function and position that content and actors occupy in a communication network often determine their influence and behavior (Kim et al. 2020). Hence, assessing the role of nodes, for example in information diffusion and cascades, is crucial (Bartal and Jagodnik 2021). The *role discovery* task first appeared in sociology since roles were used to explain the specific function of a person in society (R. A. Rossi and Ahmed 2015); then, identifying social roles became a crucial problem in social network analysis (Bartal and Jagodnik 2021; Evans et al. 2021; Y. Liu et al. 2019; Lumbreras et al. 2017; Saxena and Reddy 2021; Xie, Wu, et al. 2022; D. Yang et al. 2019). Intuitively, two nodes belong to the same role if they have similar behavior (or position; Vega, Magnani, et al. 2016) in a network. Role detection consists of grouping nodes into classes based on a given metric of equivalence or similarity (Henderson et al. 2012; R. A. Rossi and Ahmed 2015). The utility of this method relies upon detecting different communication behaviors of actors: scholars have uncovered roles like "answer-person" (Buntain and Golbeck 2014), "discussion-person" (ibid.), "information disseminators" (Y. Liu et al. 2019), "conversation facilitators" (Kou et al. 2018), content producers and consumers (Maia and Almeida 2008), and many others (Benamar et al. 2017). There are two main families of methods for role discovery: graph-based and feature-based. Graph-based methods focus on networks' topology (i.e., connectivity and structure), grouping nodes with similar connection patterns (blockmodels; R. A. Rossi and Ahmed 2015) or with similar neighbor relationships (similarity of adjacency matrix; ibid.). Feature-based methods are grounded on node equivalence and similarity metrics for feature representation (ibid.). They prioritize individual characteristics of nodes, using node attributes in the role computation, hence representing a richer and more versatile approach. More methods continue to appear in literature (Akar et al. 2019; S. Liu, Toriumi, et al. 2022; Vega, Magnani, et al. 2016), as well as new works addressing role interpretation (Cunningham and Greene 2023; Rafique et al. 2019).

Real social and communication networks are often organized in groups of nodes. *Community detection* is the problem of uncovering cohesive clusters and has been addressed using algorithms for network partitioning. Such algorithms can be classified into two major classes: disjoint — if each node is a member of exactly one community — and overlapping — if a node can belong to multiple communities — (Coscia 2021). Several methods for community detection have been proposed, many of which include the use of node semantics and attributes in addition to improving communities' quality and explainability (Jin et al. 2023; Kherad et al. 2024); dynamic community detection algorithms (Rossetti and Cazabet 2018) are utilized to identify evolving groups of nodes in temporal communication networks. The utility of such methods in social communication research encompasses grouping actors or contents that are interconnected or share similar characteristics, in order to capture insights into the structural organization of communication patterns (Panayiotou and Magnani 2024). In word co-occurrence networks, for instance, community detection algorithms are applied to detect conversation topics (Galluccio et al. 2022).

4.3 Models

In many real communication networks, new nodes entering over time are more likely to connect to existing nodes with a higher degree, creating a rich-get-richer effect, also known as *Matthew effect*. *Preferential attachment* is a generative model in network science that explains such phenomenon, leading to the emergence of scale-free networks (i.e., networks having a power-law degree distribution; Piva et al. 2021). This generates *hubs* (i.e., nodes with very high degree), mirroring social scenarios where popular actors or content (e.g., public figures or viral news) tend to gain more attention. In language evolution studies (see Section 5), preferential attachment has been used to investigate the cultural evolution of languages (Raviv et al. 2020).

Multilayer networks are expressive models that help the representation and analysis of different types of connections between nodes (Coscia 2021; P.-Z. Li et al. 2020; Lotito et al. 2022; Panayiotou, Magnani, and Pinaud 2023; Pizzuti and Socievole 2018). They consist of many layers of nodes, where each layer indicates a type of relationship between the same set of nodes (Dickison et al. 2016). Layers can be topics, temporal intervals (Russo et al. 2024), platforms, channels, or media. Layers can be analyzed separately or together to understand how relationships overlap. Given this rich representation, multilayer networks can account for several different social scenarios and environments at the same time, representing an initial effort to model context (see Section 3) in network-based communication analysis (Aleta and Moreno 2019; Amato et al. 2017; Kivelä et al. 2014). *Multilevel network* models allow for the integration of multiple sets of nodes, edges, and their connections across different layers (Lazega and Snijders 2016). They capture vertical dependencies between different network layers (representing, for example, individual and organizational levels, with both within and between-group connections).

Information dissemination processes in communication networks are usually studied by relying on *epidemic models* (Firdaniza et al. 2022; Majeed et al. 2018), the *voter model* (Du 2022; Redner 2017), and the so-called *classical diffusion models* — i.e., threshold and cascade models (Firdaniza et al. 2022; M. Li, Wang, et al. 2017; Singh, Srivastva, et al. 2022). These models have been utilized for many practical applications like studying communication activities and effects (see Section 5), as well as analyzing negative opinions spread (Luo et al. 2019) and vaccine hesitancy (Fügenschuh and F. Fu 2023). Recent variations of such models have been used to identify opinion leaders (Ruan et al. 2015; Yin et al. 2019) and analyze the role of content moderation in the spread of disinformation (Butts et al. 2023).

In order to enable a unified analysis of communication ingredients (Section 3), Vega and Magnani (2018, 2023) have proposed new network models to study communication with a comprehensive perspective, such as the Temporal Text Network model (TTN). Such a model enhances communication networks' richness by including actors, content, and time, allowing for more complete representations and analyses. TTN also provides actor-content, actor-actor, and content-content links (e.g., respectively, message creation, follower-followee relationships, and retweets), and can incorporate context by directly applying a multilayer transformation to the model.

5 Research areas and applications

We have identified seven key research areas that address specific aspects of studying social communication through network science. These areas span a wide range of disciplines, including computer science, linguistics, sociology, social psychology, sociolinguistics, and digital humanities. Such disciplines have fuzzy boundaries and do not operate in isolation: studies on social communication using network science are inherently interdisciplinary and appear across multiple domains. This collaboration enriches our understanding of social communication, as diverse perspectives contribute uniquely to exploring its complexities. While a complete review of network science applications in social communication is beyond the scope of this chapter, this section organizes key examples and highlights important research trends. The examples provided use the ingredients described in Sections 3, and metrics, methods, and models discussed in Section 4. Specifically, we selected examples that focus on real-world communication, using non-synthetic, non-random social networks to ground the discussion.

1. *Developing theoretical frameworks for communication networks.* This area focuses on synthesizing research findings on social communication into cohesive theoretical frameworks (S. Choi 2020; Locher 2015). Scholars work on creating and refining network science tools, methodologies, and techniques for studying communication (Pagan et al. 2021; Rani and Shokeen 2021; Roller and Schweitzer 2021; Sherry 2015; Zeng et al. 2022), producing foundational knowledge that helps explain social communication phenomena like the role of reciprocity in trust-building and information exchange (Feng et al. 2014). Research in this area has also significantly advanced our understanding of how communication networks evolve, thanks to the development of models and metrics that capture the temporal and spatial dimensions of interactions.

2. *Studying interactional organization.* Researchers explore how actors manage communication exchanges, particularly in digital spaces where technological affordances may both restrict and empower interactions (Foucault Welles and González-Bailón 2020; Locher 2015), and where platform limitations prompt the development of new norms and strategies to organize interactions (Goglia and Vega 2024). They analyze how people participate in multiparty collaborative conversations (Belkaroui et al. 2015) creating and maintaining coherence and flow (Brambilla et al. 2022; Childs 2016; Iorio 2016; Nguyen 2022). Studies in this area address turn-taking and interruptions (Haddington et al. 2023; Jakonen and Niemi 2020; O'Bryan et al. 2022; Tian et al. 2024), as well as the use of non-textual material such as emoticons (Beißwenger and Pappert 2019; Gibson 2024; Haddington et al. 2023). For example, posting incomplete sentences is a common and effective strategy for managing turn-taking, signaling that more is to come (Locher 2015).

3. *Analyzing communication activities and their effects.* This area examines the functional use of content to achieve social actions, such as disagreeing (Anderson and Ye 2019; Lorentzen 2021), persuading (Monti et al. 2022) or giving advice (Xu et al. 2023). This includes both the active participant, who uses communication to achieve specific goals, and the passive actor, who experiences the effects. Actors' behavior is analyzed in terms of both actively pursuing objectives and passively experiencing the communication impact (Novotná et al. 2023). The analysis of communication networks allows researchers in this area to produce significant findings on how linguistic actions shape individual and collective behavior (La Cava et al. 2023), providing actionable insights into societal challenges such as misinformation and social coordination. Scholars have indeed uncovered patterns of connectivity that drive phenomena like polarization (Bliuc et al. 2024; Edelmann et al. 2020), information dissemination (S. Peng et al. 2017), and collective actions (Bail et al. 2018; Rabb et al. 2023; Ramaciotti et al. 2024; Tardelli et al. 2024).

4. *Investigating situated interpersonal language use.* This area examines how communication expresses identity (Locher and Bolander 2015; Yus 2018), establishes group membership (Edelmann et al. 2020), and builds and maintains relationships (Collister 2016; Mullan 2024; Tanskanen et al. 2024). For instance, users in online gaming communities often adopt specific jargon or slang to signal belonging (Childs 2016; Iorio 2016). Community detection algorithms and percolation (Section 4.2) have been applied to, respectively (i) analyze code-switching patterns in multilingual communities, revealing how language choices both reflect and reinforce social group boundaries (Z. Yang et al. 2016), and (ii) investigate the role of social contact in the emergence of cooperation in gaming (H.-X. Yang and J. Yang 2019). The resulting knowledge from this area sheds light on complex social and psychological mechanisms surrounding social communication, significantly advancing our understanding of how language serves as a social tool to construct and express personality, reinforce cohesion, and navigate social contexts. Network analysis has shown, for example, that dense communication networks within groups reinforce shared norms and linguistic practices, strengthening group identity (Smith et al. 2020).

5. *Exploring various modes of social communication.* By modeling interactions occurring in diverse modes — chats, blogs, emails — with networks, researchers investigate how design features influence communication. Studies explore how each mode impacts communication (Maíz-Arévalo 2019), including limitations on message length, and fostering distinct styles. As new modes emerge and existing ones evolve, this area examines how platform design shapes communication and how different media features influence users' behavior affecting their discussion patterns (Chowdhary et al. 2023; Goglia and Vega 2024; Locher 2014; Medvedev et al. 2018; Shevtsov et al. 2023). For instance, Aragón et al. (2017) used reciprocity metrics on conversation graphs to study a Spanish news platform, finding a significant increase in reciprocal communication after the introduction of a threaded interface. Contributions in this area also revealed the profound impact that multimodal communication has in conveying meaning and disseminating knowledge through different channels (Meredith 2019). These insights have broader implications for understanding how platform architecture can either promote or hinder communication richness, affecting how information is constructed and shared.

6. *Studying language evolution.* Digital communication accelerates linguistic changes, facilitating the spread of new slang (Awal et al. 2020; Bieswanger 2016; Bohmann 2016; Cutler 2016, 2022; Hinrichs 2016; Iorio 2016). Networks at lexical, phonological, and semantic levels, with both actor-actor and content-content links, have been used to study language evolution and the emergence of specific linguistic features (Al Rozz et al. 2017; H. Chen 2023; Choudhury and Mukherjee 2009; Cong and H. Liu 2014; Raviv et al. 2020; Shadrova 2022). In particular, this area has highlighted the role of digital communication as a catalyst for linguistic creativity, allowing for the rapid diffusion of new expressions and transforming traditional language norms.

7. *Creating and maintaining datasets and corpora.* Researchers collect and curate network data that represent various types of social communication (Chang et al. 2020; Leskovec and Krevl 2014; Peixoto 2024), ensuring high-quality datasets for modeling and analyzing communication networks. Contributions from this area played a crucial role in establishing the foundational data that enable modeling and analyzing social communication networks. Such data constitute the key resource for reproducible and openly accessible research.

6 Conclusion

In this chapter, we have discussed network science as a valuable framework for communication analysis, bringing structure to diverse aspects of the field. We outlined the five ingredients of communication analysis — actors, content, links, time, and context — (Section 3), challenging conventional network-based representations and promoting a richer and more versatile approach to address the complexity of communication. We reviewed network metrics, methods, and models commonly used to answer complex questions in the field (Section 4). Finally, we highlighted and organized a selection of network science applications to communication studies (Section 5). Through this exploration, we aim to contribute to a deeper understanding of how network science can continue to evolve and enrich the study of social communication, especially in the digital age. We hope to encourage thoughtful reflection on the current landscape of network-based approaches for understanding and analyzing contemporary communication.

Acknowledgment

This work has been partly funded by eSSENCE, an e-Science collaboration funded as a strategic research area of Sweden. The funders had no role in the study design, decision to publish, or preparation of the manuscript.

References

Aiello, L. M. (2015). Group Types in Social Media. In *User Community Discovery* (pp. 97–134). Springer International Publishing. https://doi.org/10.1007/978-3-319-23835-7_5

Akar, E., Mardikyan, S., & Dalgic, T. (2019). User Roles in Online Communities and Their Moderating Effect on Online Community Usage Intention: An Integrated Approach. *International Journal of Human–Computer Interaction*, *35*(6), 495–509. https://doi.org/10.1080/10447318.2018.1465325

Al Rozz, Y., Hamoodat, H., & Menezes, R. (2017). Characterization of Written Languages Using Structural Features from Common Corpora. *Complex Networks VIII*, 161–173. https://doi.org/10.1007/978-3-319-54241-6_14

Aleta, A., & Moreno, Y. (2019). Multilayer networks in a nutshell. *Annual Review of Condensed Matter Physics*, *10*(1), 45–62.

Amato, R., Kouvaris, N. E., San Miguel, M., & Díaz-Guilera, A. (2017). Opinion competition dynamics on multiplex networks. *New Journal of Physics*, *19*(12).

Anderson, B. D. O., & Ye, M. (2019). Recent Advances in the Modelling and Analysis of Opinion Dynamics on Influence Networks. *International Journal of Automation and Computing*, *16*(2), 129–149. https://doi.org/10.1007/s11633-019-1169-8

Aragón, P., Gómez, V., & Kaltenbrunner, A. (2017). To Thread or Not to Thread: The Impact of Conversation Threading on Online Discussion. *Proceedings of the International AAAI Conference on Web and Social Media*, *11*(1), 12–21. https://doi.org/10.1609/icwsm.v11i1.14880

Arminio, L., Magnani, M., Piqueras, M., Rossi, L., & Segerberg, A. (2024). Leveraging VLLMs for Visual Clustering: Image-to-text mapping shows increased semantic capabilities and interpretability. https://osf.io/bf459/download

Aswath, S., Godavarthi, D., & Das, B. (2020). Analysing Conflicts in Online Football Communities of Reddit. *2020 ic-ETITE*, 1–6. https://doi.org/10.1109/ic-ETITE47903.2020.386

Awal, M. R., Cao, R., Mitrovic, S., & Lee, R. K.-W. (2020). On Analyzing Antisocial Behaviors Amid COVID-19 Pandemic. https://doi.org/10.48550/arXiv.2007.10712

Bail, C. A., Argyle, L. P., Brown, T. W., Bumpus, J. P., Chen, H., Hunzaker, M. B. F., Lee, J., Mann, M., Merhout, F., & Volfovsky, A. (2018). Exposure to opposing views on social media can increase political polarization. *Proceedings of the National Academy of Sciences*, *115*(37), 9216–9221. https://doi.org/10.1073/pnas.1804840115

Banisch, S., & Olbrich, E. (2019). Opinion polarization by learning from social feedback. *The Journal of Mathematical Sociology*, *43*(2), 76–103. https://doi.org/10.1080/0022250X.2018.1517761

Barbucha, D., & Szyman, P. (2021). Identifying Key Actors in Organizational Social Network Based on E-Mail Communication. *Advances in Computational Collective Intelligence*, 3–14. https://doi.org/10.1007/978-3-030-88113-9_1

Bartal, A., & Jagodnik, K. M. (2021). Role-Aware Information Spread in Online Social Networks. *Entropy*, *23*(11). https://doi.org/10.3390/e23111542

Beißwenger, M., & Pappert, S. (2019). How to be polite with emojis: A pragmatic analysis of face work strategies in an online learning environment. *European Journal of Applied Linguistics*, *7*(2), 225–254. https://doi.org/doi:10.1515/eujal-2019-0003

Belkaroui, R., Faiz, R., & Elkhlifi, A. (2015). Social users interactions detection based on conversational aspects. *Studies in Computational Intelligence*, *598*. https://doi.org/10.1007/978-3-319-16211-9_17

Benamar, L., Balagué, C., & Ghassany, M. (2017). The Identification and Influence of Social Roles in a Social Media Product Community. https://doi.org/10.1111/jcc4.12195

Bieswanger, M. (2016). Electronically-mediated englishes: Synchronicity revisited. In *English in computer-mediated communication: Variation, representation, and change* (pp. 281–300). De Gruyter. https://doi.org/doi:10.1515/9783110490817-013

Bliuc, A.-M., Betts, J. M., Vergani, M., Bouguettaya, A., & Cristea, M. (2024). A theoretical framework for polarization as the gradual fragmentation of a divided society. *Communications Psychology*, *2*(1), 75. https://doi.org/10.1038/s44271-024-00125-1

Boekhout, H., Traag, V., & Takes, F. (2021). Investigating scientific mobility in co-authorship networks using multilayer temporal motifs. *Network Science*, *9*, 354–386. https://doi.org/10.1017/nws.2021.12

Bohmann, A. (2016). Language change because twitter? factors motivating innovative uses of because across the english-speaking twittersphere. In *English in computer-mediated communication: Variation, representation, and change* (pp. 149–178). De Gruyter. https://doi.org/doi:10.1515/9783110490817-008

Bolander, B., & Locher, M. A. (2014). Doing sociolinguistic research on computer-mediated data: A review of four methodological issues. *Discourse, Context Media*, *3*, 14–26. https://doi.org/10.1016/j.dcm.2013.10.004

Bolander, B., & Locher, M. A. (2020). Beyond the online offline distinction: Entry points to digital discourse. *Discourse, Context Media*, *35*. https://doi.org/10.1016/j.dcm.2020.100383

Borgatti, S., Everett, M., & Johnson, J. (2018). *Analyzing social networks*. SAGE Publications.

Borgatti, S. P., Mehra, A., Brass, D. J., & Labianca, G. (2009). Network Analysis in the Social Sciences. *Science*, *323*(5916), 892–895. https://doi.org/10.1126/science.1165821

boyd, D. (2010). Social network sites as networked publics: Affordances, dynamics, and implications. In *A networked self* (pp. 47–66). Routledge.

Brambilla, M., Javadian Sabet, A., Kharmale, K., & Sulistiawati, A. E. (2022). Graph-Based Conversation Analysis in Social Media. *Big Data and Cognitive Computing*, *6*(4). https://doi.org/10.3390/bdcc6040113

Buntain, C., & Golbeck, J. (2014). Identifying social roles in reddit using network structure. *Proceedings of the 23rd International Conference on World Wide Web*, 615–620. https://doi.org/10.1145/2567948.2579231

Butts, D. J., Bollman, S. A., & Murillo, M. S. (2023). Mathematical modeling of disinformation and effectiveness of mitigation policies. *Scientific Reports*, *13*(1). https://doi.org/10.1038/s41598-023-45710-2

Cannon, B. C., & Robinson, D. T. (2023). A simplest mathematics of turn-taking: Conversational deep structure, emergence, and permeation. *Network Science*, *11*(2), 224–248. https://doi.org/10.1017/nws.2022.38

Chalakudi, S., Hussain, D., Bharathy, G., & Kolluru, M. (2023). Measuring Social Influence in Online Social Networks - Focus on Human Behavior Analytics. *Association of Marketing Theory and Practice Proceedings 2023*. https://digitalcommons.georgiasouthern.edu/amtp-proceedings_2023/9

Chang, J. P., Chiam, C., Fu, L., Wang, A., Zhang, J., & Danescu-Niculescu-Mizil, C. (2020). Convokit: A toolkit for the analysis of conversations. *Proceedings of SIGDIAL*.

Chen, H. (2023). A lexical network approach to second language development. *Humanities and Social Sciences Communications*, *10*(1). https://doi.org/10.1057/s41599-023-02151-6

Chen, Y., Kmetty, Z., Iniguez, G., & Omodei, E. (2024). The Public that Engages Invisibly: What Visible Engagement Fails to Capture in Online Political Communication. https://doi.org/10.31235/osf.io/mv24c

Childs, B. (2016). Who i am and who i want to be: Variation and representation in a messaging platform. In *English in computer-mediated communication: Variation, representation, and change* (pp. 261–278). De Gruyter. https://doi.org/doi:10.1515/9783110490817-012

Choi, D., Han, J., Chung, T., Ahn, Y.-Y., Chun, B.-G., & Kwon, T. T. (2015). Characterizing conversation patterns in reddit: From the perspectives of content properties and user participation behaviors. *Proceedings of the 2015 ACM on Conference on Online Social Networks*. https://doi.org/10.1145/2817946.2817959

Choi, S. (2020). When Digital Trace Data Meet Traditional Communication Theory: Theoretical/Methodological Directions. *Social Science Computer Review*, *38*(1), 91–107. https://doi.org/10.1177/0894439318788618

Choudhury, M., & Mukherjee, A. (2009). The Structure and Dynamics of Linguistic Networks. In *Dynamics On and Of Complex Networks* (pp. 145–166). Birkhäuser Boston. https://doi.org/10.1007/978-0-8176-4751-3_9

Chowdhary, S., Andres, E., Manna, A., Blagojević, L., Di Gaetano, L., & Iñiguez, G. (2023). Temporal patterns of reciprocity in communication networks. *EPJ Data Science*, *12*(1), 1–15. https://doi.org/10.1140/epjds/s13688-023-00382-w

Cinelli, M., De Francisci Morales, G., Galeazzi, A., Quattrociocchi, W., & Starnini, M. (2021). The echo chamber effect on social media. *Proceedings of the National Academy of Sciences*, *118*(9).

Cobley, P., & Schulz, P. J. (Eds.). (2013). *Theories and models of communication*. De Gruyter. https://doi.org/doi:10.1515/9783110240450

Collister, L. B. (2016). "at least i'm not chinese, gay, or female": Marginalized voices in world of warcraft. In *English in computer-mediated communication: Variation, representation, and change* (pp. 351–376). De Gruyter. https://doi.org/doi:10.1515/9783110490817-016

Cong, J., & Liu, H. (2014). Approaching human language with complex networks. *Physics of Life Reviews*, *11*(4), 598–618. https://doi.org/10.1016/j.plrev.2014.04.004

Contractor, N., Monge, P., & Leonardi, P. (2011). Multidimensional networks and the dynamics of sociomateriality: Bringing technology inside the network. *International Journal of Communication*, *5*(0). https://ijoc.org/index.php/ijoc/article/view/1131

Coscia, M. (2021). The Atlas for the Aspiring Network Scientist. https://doi.org/10.48550/arXiv.2101.00863

Coscia, M., & Szell, M. (2021). Multilayer Graph Association Rules for Link Prediction. *Proceedings of the International AAAI Conference on Web and Social Media*, *15*, 129–139. https://doi.org/10.1609/icwsm.v15i1.18047

Cota, W., Ferreira, S. C., Pastor-Satorras, R., & Starnini, M. (2019). Quantifying echo chamber effects in information spreading over political communication networks. *EPJ Data Science*, *8*(1). https://doi.org/10.1140/epjds/s13688-019-0213-9

Cunningham, E., & Greene, D. (2023). Surrogate explanations for role discovery on graphs. *Applied Network Science*, *8*(1), 1–17. https://doi.org/10.1007/s41109-023-00551-w

Cutler, C. (2016). Ets jast ma booooooooooooo: Social meanings of scottish accents on youtube. In *English in computer-mediated communication: Variation, representation, and change* (pp. 69–98). De Gruyter. https://doi.org/doi:10.1515/9783110490817-005

Cutler, C. (2022). Orality, alignment, and stance in youtube comments about the new york city accent. In *Digital orality: Vernacular writing in online spaces* (pp. 159–187). Springer International Publishing. https://doi.org/10.1007/978-3-031-10433-6_6

Dickison, M. E., Magnani, M., & Rossi, L. (2016). *Multilayer social networks*. Cambridge University Press.

Du, J. (2022). Voter model on adaptive networks. *Chinese Physics B*, *31*(5). https://doi.org/10.1088/1674-1056/ac43b4

Edelmann, A., Wolff, T., Montagne, D., & Bail, C. A. (2020). Computational Social Science and Sociology. *Annual Review of Sociology*, *46*(1), 61–81. https://doi.org/10.1146/annurev-soc-121919-054621

Erkan, G., & Radev, D. R. (2011). LexRank: Graph-based Lexical Centrality as Salience in Text Summarization. https://doi.org/10.48550/arXiv.1109.2128

Evans, E., Guo, W., Genctav, A., Tari, S., Domeniconi, C., Murillo, A., Chuang, J., AlSumait, L., Mani, P., & El-Zehiry, N. (2021). Role Detection and Prediction in Dynamic Political Networks. In *Advances in Data Science* (pp. 233–252). Springer International Publishing. https://doi.org/10.1007/978-3-030-79891-8_10

Feng, X., Zhao, J., Fang, Z., & Xu, K. (2014). Time-aware reciprocity prediction in trust network. *2014 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM 2014)*, 234–237.

Firdaniza, F., Ruchjana, B. N., Chaerani, D., & Radianti, J. (2022). Information Diffusion Model in Twitter: A Systematic Literature Review. *Information*, *13*(1). https://doi.org/10.3390/info13010013

Foucault Welles, B., & González-Bailón, S. (2020). *The Oxford Handbook of Networked Communication*. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780190460518.001.0001

Francis, T., Davidson, M., Senese, L., Jeffs, L., Yousefi-Nooraie, R., Ouimet, M., Rac, V., & Trbovich, P. (2024). Exploring the use of social network analysis methods in process improvement within healthcare organizations: A scoping review. *BMC Health Services Research*, *24*(1). https://doi.org/10.1186/s12913-024-11475-1

Fronzetti Colladon, A., & Gloor, P. A. (2019). Measuring the impact of spammers on e-mail and Twitter networks. *International Journal of Information Management*, *48*, 254–262. https://doi.org/10.1016/j.ijinfomgt.2018.09.009

Fu, Y., & Huang, J. (2024). TeMotif: An Efficient Approach to Temporal Motif Matching. *2024 IEEE International Conference on Sensing, Diagnostics, Prognostics, and Control (SDPC)*, 8–14. https://doi.org/10.1109/SDPC62810.2024.10707723

Fudolig, M. I., Alshaabi, T., Arnold, M. V., Danforth, C. M., & Dodds, P. S. (2022). Sentiment and structure in word co-occurrence networks on Twitter. *Applied Network Science*, *7*(1), 1–27. https://doi.org/10.1007/s41109-022-00446-2

Fügenschuh, M., & Fu, F. (2023). Overcoming vaccine hesitancy by multiplex social network targeting: An analysis of targeting algorithms and implications. *Applied Network Science*, *8*(1), 1–19. https://doi.org/10.1007/s41109-023-00595-y

Galluccio, C., Magnani, M., Vega, D., Ragozini, G., & Petrucci, A. (2022). Robustness and sensitivity of network-based topic detection. *International Conference on Complex Networks and Their Applications*.

Gibson, W. (2024). Flirting and winking in tinder chats: Emoji, ambiguity, and sequential actions. *Internet Pragmatics*. https://doi.org/10.1075/ip.00107.gib

Goglia, D., & Vega, D. (2024). Structure and dynamics of growing networks of Reddit threads. *Applied Network Science*, *9*(1), 1–23. https://doi.org/10.1007/s41109-024-00654-y

Grobelny, J., & Michalski, R. (2022). Linguistic patterns as a framework for an expert knowledge representation in agent movement simulation. *Knowledge-Based Systems*, *243*. https://doi.org/10.1016/j.knosys.2022.108497

Haddington, P., Eilittä, T., Kamunen, A., Kohonen-Aho, L., Rautiainen, I., & Vatanen, A. (2023). *Complexity of interaction: Studies in multimodal conversation analysis* (1st). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-30727-0

Hanteer, O., Rossi, L., D'Aurelio, D. V., & Magnani, M. (2018a). From interaction to participation: The role of the imagined audience in social media community detection and an application to political communication on twitter. *2018 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*. https://doi.org/10.1109/ASONAM.2018.8508575

Hanteer, O., Rossi, L., D'Aurelio, D. V., & Magnani, M. (2018b). From Interaction to Participation: The Role of the Imagined Audience in Social Media Community Detection and an Application to Political Communication on Twitter. *2018 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*, 531–534. https://doi.org/10.1109/ASONAM.2018.8508575

Helbing, D., Brockmann, D., Chadefaux, T., Donnay, K., Blanke, U., Woolley-Meza, O., Moussaid, M., Johansson, A., Krause, J., Schutte, S., & Perc, M. (2015). Saving Human Lives: What Complexity Science and Information Systems can Contribute. *Journal of Statistical Physics*, *158*(3), 735–781. https://doi.org/10.1007/s10955-014-1024-9

Henderson, K., Gallagher, B., Eliassi-Rad, T., Tong, H., Basu, S., Akoglu, L., Koutra, D., Faloutsos, C., & Li, L. (2012). RolX: Structural role extraction & mining in large graphs. *Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining*, 1231–1239. https://doi.org/10.1145/2339530.2339723

Hepp, A., Loosen, W., Dreyer, S., Jarke, J., Kannengießer, S., Katzenbach, C., Malaka, R., Pfadenhauer, M. P., Puschmann, C., & Schulz, W. (2023). ChatGPT, LaMDA, and the Hype Around Communicative AI: The Automation of Communication as a Field of Research in Media and Communication Studies. *Human-Machine Communication*, *6*, 41–63. https://doi.org/10.30658/hmc.6.4

Hilbert, M., Barnett, G., Blumenstock, J., Contractor, N., Diesner, J., Frey, S., González-Bailón, S., Lamberson, P. J., Pan, J., Peng, T.-Q., Shen, C. (, Smaldino, P. E., Van Atteveldt, W., Waldherr, A., Zhang, J., & Zhu, J. J. H. (2019). Computational Communication Science— Computational Communication Science: A Methodological Catalyzer for a Maturing Discipline. *International Journal of Communication*, *13*(0). https://ijoc.org/index.php/ijoc/article/view/10675

Himelboim, I., & Golan, G. J. (2019). A social networks approach to viral advertising: The role of primary, contextual, and low influencers. *Social Media + Society*, *5*(3). https://doi.org/10.1177/2056305119847516

Hinrichs, L. (2016). Modular repertoires in english-using social networks: A study of language choice in the networks of adult facebook users. In *English in computer-mediated communication* (pp. 17–42). De Gruyter. https://doi.org/doi:10.1515/9783110490817-003

Hohmann, M., Devriendt, K., & Coscia, M. (2023). Quantifying ideological polarization on a network using generalized Euclidean distance. *Science Advances*, *9*(9). https://doi.org/10.1126/sciadv.abq2044

Holme, P., & Saramäki, J. (2012). Temporal networks. *Physics Reports*, *519*(3), 97–125. https://doi.org/10.1016/j.physrep.2012.03.001

Hu, Y., Ji, S., Jin, Y., Feng, L., Stanley, H. E., & Havlin, S. (2018). Local structure can identify and quantify influential global spreaders in large scale social networks. *Proceedings of the National Academy of Sciences*, *115*(29), 7468–7472. https://doi.org/10.1073/pnas.1710547115

Iñiguez, G., Heydari, S., Kertész, J., & Saramäki, J. (2023). Universal patterns in egocentric communication networks. *Nature Communications*, *14*(1). https://doi.org/10.1038/s41467-023-40888-5
Iorio, J. (2016). Implications of attitudes about non-standard english on interactional structure in the computer-mediated workplace: A story of two modes. In *English in computer-mediated communication: Variation, representation, and change* (pp. 327–350). De Gruyter. https://doi.org/doi:10.1515/9783110490817-015
Jakonen, T., & Niemi, K. (2020). Managing participation and turn-taking in children's digital activities. *Social Interaction. Video-Based Studies of Human Sociality*, *3*(1). https://doi.org/10.7146/si.v3i1.120250
Jin, D., Yu, Z., Jiao, P., Pan, S., He, D., Wu, J., Yu, P. S., & Zhang, W. (2023). A survey of community detection approaches: From statistical modeling to deep learning. https://doi.org/10.1109/TKDE.2021.3104155
Jung, S., & Segev, A. (2022). Semantic similarity analysis between future topics and their neighbors in topic networks for network-based topic evolution. *2022 IEEE International Conference on Big Data (Big Data)*, 5952–5961. https://doi.org/10.1109/BigData55660.2022.10020287
Kapucu, N., Dougherty, R. B., Ge, Y., & Zobel, C. (2023). The use of documentary data for network analysis in emergency and crisis management. *Natural Hazards*, *116*(1), 425–445. https://doi.org/10.1007/s11069-022-05681-5
Kherad, M., dadras, M., & Mokhtari, M. (2024). Community detection based on influential nodes in dynamic networks. *The Journal of Supercomputing*, *80*(16), 24664–24688. https://doi.org/10.1007/s11227-024-06367-4
Kim, H. M., Ryou, E., Yi, K.-H., & Ahn, S.-K. (2020). Visualizing Social Roles and Structural Signatures of the Cosmetic Brands on the Sephora's' Twitter. *International Textile and Apparel Association Annual Conference Proceedings*, *77*(1). https://doi.org/10.31274/itaa.11712
Kivelä, M., Arenas, A., Barthelemy, M., Gleeson, J. P., Moreno, Y., & Porter, M. A. (2014). Multilayer networks. *Journal of Complex Networks*, *2*(3), 203–271. https://doi.org/10.1093/comnet/cnu016
Kou, Y., Gray, C. M., Toombs, A. L., & Adams, R. S. (2018). Understanding social roles in an online community of volatile practice: A study of user experience practitioners on reddit. *Trans. Soc. Comput.*, *1*(4). https://doi.org/10.1145/3283827
Kubota, M. (2019). What is" communication"?-beyond the shannon & weaver's model. *International Journal for Educational Media and Technology*, *13*(1). https://jaems.jp/contents/icomej/vol13/06_Kubota.pdf
Kumar, A., Singh, S. S., Singh, K., & Biswas, B. (2020). Link prediction techniques, applications, and performance: A survey. *Physica A: Statistical Mechanics and its Applications*, *553*. https://doi.org/10.1016/j.physa.2020.124289
Kumar, S., Natrajan, P., & Gupta, P. (2024). Quantification and measurement of relationship between movies and actors for production resources optimisation and box office business success. *Social Network Analysis and Mining*, *14*(1). https://doi.org/10.1007/s13278-024-01232-x
La Cava, L., Aiello, L. M., & Tagarelli, A. (2023). Drivers of social influence in the twitter migration to mastodon. *Scientific Reports*, *13*(1). https://doi.org/10.1038/s41598-023-48200-7
Lazega, E., & Snijders, T. (2016). *Multilevel Network Analysis for the Social Sciences*. Springer International Publishing. https://doi.org/10.1007/978-3-319-24520-1
Leskovec, J., & Krevl, A. (2014). SNAP Datasets: Stanford large network dataset collection. http://snap.stanford.edu/data
Li, J., Qi, J., Huang, Y., Cao, L., Yu, Y., & Dong, J. (2024). MoTTo: Scalable Motif Counting with Time-aware Topology Constraint for Large-scale Temporal Graphs. *Proceedings of the 33rd ACM International Conference on Information and Knowledge Management*, 1195–1204. https://doi.org/10.1145/3627673.3679694
Li, M., Wang, X., Gao, K., & Zhang, S. (2017). A Survey on Information Diffusion in Online Social Networks: Models and Methods. *Information*, *8*(4). https://doi.org/10.3390/info8040118
Li, M., Liu, R.-R., Lü, L., Hu, M.-B., Xu, S., & Zhang, Y.-C. (2021). Percolation on complex networks: Theory and application. *Physics Reports*, *907*, 1–68. https://doi.org/10.1016/j.physrep.2020.12.003
Li, P.-Z., Huang, L., Wang, C.-D., Lai, J.-H., & Huang, D. (2020). Community detection by motif-aware label propagation. *ACM Trans. Knowl. Discov. Data*, *14*(2). https://doi.org/10.1145/3378537
Li, X., Zhou, S., Liu, J., Chen, G., Gu, Z., & Wang, Y. (2019). A new metric to quantify influence of nodes in social networks. *International Journal of Modern Physics B*, (17). https://doi.org/10.1142/S0217979219501868
Li, X., Liu, Y., Jiang, Y., & Liu, X. (2016). Identifying social influence in complex networks: A novel conductance eigenvector centrality model. *Neurocomputing*, *210*, 141–154. https://doi.org/10.1016/j.neucom.2015.11.123
Li, Z., Yan, Z., Yang, J., & Tang, X. (2024). The Structure Entropy of Social Networks. *Journal of Systems Science and Complexity*, *37*(3), 1147–1162. https://doi.org/10.1007/s11424-024-2484-x
Liu, S., Toriumi, F., Nishiguchi, M., & Usui, S. (2022). A flexible framework for multiple-role discovery in real networks. *Applied Network Science*, *7*(1), 1–23. https://doi.org/10.1007/s41109-022-00509-4

Liu, S., Zhang, D., Tian, Y., Xu, B., & Wu, X. (2023). Gender differences in symptom structure of adolescent problematic internet use: A network analysis. *Child and Adolescent Psychiatry and Mental Health*, *17*. https://doi.org/10.1186/s13034-023-00590-2

Liu, Y., Fei, D., Sun, J., Silva, T., Jiang, Y., & Zhu, T. (2019). Identifying social roles using heterogeneous features in online social networks. *Journal of the Association for Information Science and Technology*, *70*. https://doi.org/10.1002/asi.24160

Locher, M. A. (2014). Electronic discourse. In *Pragmatics of discourse* (pp. 555–581). Mouton.

Locher, M. A. (2015). Language and communication in computer- mediated contexts: A rich and challenging research field. *International Journal of English Studies*.

Locher, M. A., & Bolander, B. (2015). Humour in microblogging: Exploiting linguistic humour strategies for identity construction in two facebook focus groups. In *Participation in public and social media interactions* (pp. 135–155, Vol. 256). John Benjamins. https://doi.org/10.1075/pbns.256.06loc

Lorentzen, D. G. (2021). Bridging polarised twitter discussions: The interactions of the users in the middle. *Aslib Journal of Information Management*, *73*(2). https://doi.org/10.1108/AJIM-05-2020-0154

Lotito, Q. F., Musciotto, F., Montresor, A., & Battiston, F. (2022). Higher-order motif analysis in hypergraphs. *Communications Physics*, *5*(1), 1–8. https://doi.org/10.1038/s42005-022-00858-7

Lumbreras, A., Jouve, B., Velcin, J., & Guégan, M. (2017). Role detection in online forums based on growth models for trees. *Social Network Analysis and Mining*, *7*(1). https://doi.org/10.1007/s13278-017-0472-z

Luo, J., Liu, X., & Kong, X. (2019). Competitive opinion maximization in social networks. *Proceedings of the 2019 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining*, 250–257. https://doi.org/10.1145/3341161.3342899

Magnani, M., Montesi, D., & Rossi, L. (2012). Conversation retrieval for microblogging sites. *Information Retrieval*, *15*(3-4), 354–372. https://doi.org/10.1007/s10791-012-9189-9

Maia, M., & Almeida, V. (2008). Identifying user behavior in online social networks. *Proceedings of the 1st Workshop on Social Network Systems*. https://doi.org/10.1145/1435497.1435498

Maíz-Arévalo, C. (2019). Losing face on facebook: Linguistic strategies to repair face in a spanish common interest group. In *Analyzing digital discourse: New insights and future directions* (pp. 283–309). Springer International Publishing. https://doi.org/10.1007/978-3-319-92663-6_10

Majeed, S., Qamar, U., & Farooq, A. (2018). State of Art Techniques for Social Influence Analysis: A Systematic Literature Review. *2018 International Conference on Frontiers of Information Technology (FIT)*, 200–205. https://doi.org/10.1109/FIT.2018.00042

Maoz, Z. (2017). Network science and international relations. https://doi.org/10.1093/acrefore/9780190228637.013.517

Martirano, L., La Cava, L., & Tagarelli, A. (2023). Evolution of the Social Debate on Climate Crisis. *2023 ICT-DM*, 1–6. https://doi.org/10.1109/ICT-DM58371.2023.10286927

Medvedev, A. N., Delvenne, J.-C., & Lambiotte, R. (2018). Modelling structure and predicting dynamics of discussion threads in online boards. *Journal of Complex Networks*, *7*(1), 67–82. https://doi.org/10.1093/comnet/cny010

Meredith, J. (2019). Conversation Analysis and Online Interaction. *Research on Language and Social Interaction*, *52*(3), 241–256. https://doi.org/10.1080/08351813.2019.1631040

Monti, C., Aiello, L. M., De Francisci Morales, G., & Bonchi, F. (2022). The language of opinion change on social media under the lens of communicative action. *Scientific Reports*, *12*(1). https://doi.org/10.1038/s41598-022-21720-4

Mullan, K. (2024). "resident superhero": Community veneration on facebook. *Internet Pragmatics*, *7*(1), 63–100. https://doi.org/10.1075/ip.00112.mul

Münch, F. V., & Rossi, L. (2020). A tale of two twitters? identifying bridges between language based twitterspheres. *AoIR Selected Papers of Internet Research*. https://doi.org/10.5210/spir.v2020i0.11283

Nguyen, H. (2022). Exploring Group Discussion with Conversational Agents Using Epistemic Network Analysis. *Advances in Quantitative Ethnography*, 378–394. https://doi.org/10.1007/978-3-030-93859-8_25

Novotná, M., Macková, A., & Rossini, P. (2023). Incivility and Intolerance in COVID-19 Discussions on Facebook. *Social Media + Society*, *9*(4). https://doi.org/10.1177/20563051231207848

Nwala, A. C., Flammini, A., & Menczer, F. (2023). A language framework for modeling social media account behavior. *EPJ Data Science*, *12*(1). https://doi.org/10.1140/epjds/s13688-023-00410-9

O'Bryan, L., Segarra, S., Paoletti, J., Zajac, S., Beier, M. E., Sabharwal, A., Wettergreen, M., & Salas, E. (2022). Conversational turn-taking as a stochastic process on networks. *2022 56th Asilomar Conference on Signals, Systems, and Computers*, 1243–1247.

Oh, P., & Monge, P. (2016). Network Theory and Models. In *The International Encyclopedia of Communication Theory and Philosophy* (pp. 1–15). John Wiley & Sons, Ltd. https://doi.org/10.1002/9781118766804.wbiect246

Pacheco, D., Hui, P.-M., Torres-Lugo, C., Truong, B. T., Flammini, A., & Menczer, F. (2021). Uncovering Coordinated Networks on Social Media: Methods and Case Studies. *Proceedings of the International AAAI Conference on Web and Social Media*, *15*, 455–466. https://doi.org/10.1609/icwsm.v15i1.18075

Pagan, N., Mei, W., Li, C., & Dörfler, F. (2021). A meritocratic network formation model for the rise of social media influencers. *Nature Communications*, *12*(1). https://doi.org/10.1038/s41467-021-27089-8

Panayiotou, G., & Magnani, M. (2024). Fair-mod: Fair modular community detection. *International Conference on Complex Networks and Their Applications*.

Panayiotou, G., Magnani, M., & Pinaud, B. (2023). Towards efficient multilayer network data management. *French Regional Conference on Complex Systems FRCCS 2023*.

Park, P. S., Blumenstock, J. E., & Macy, M. W. (2018). The strength of long-range ties in population-scale social networks. *Science*, *362*(6421), 1410–1413. https://doi.org/10.1126/science.aau9735

Peel, L., Peixoto, T., & De Domenico, M. (2022). Statistical inference links data and theory in network science. *Nature Communications*, *13*(1). https://doi.org/10.1038/s41467-022-34267-9

Peixoto, T. (2024). Netzschleuder. https://networks.skewed.de

Peng, S., Yang, A., Cao, L., Yu, S., & Xie, D. (2017). Social influence modeling using information theory in mobile social networks. *Information Sciences*, *379*, 146–159. https://doi.org/10.1016/j.ins.2016.08.023

Perikos, I., & Michael, L. (2022). A Survey on Tie Strength Estimation Methods in Online Social Networks: *Proceedings of the 14th International Conference on Agents and Artificial Intelligence*, 484–491. https://doi.org/10.5220/0010845100003116

Perna, D., Interdonato, R., & Tagarelli, A. (2018). Identifying Users With Alternate Behaviors of Lurking and Active Participation in Multilayer Social Networks. *IEEE Transactions on Computational Social Systems*, *5*(1), 46–63. https://doi.org/10.1109/TCSS.2017.2762730

Piva, G. G., Ribeiro, F. L., & Mata, A. S. (2021). Networks with growth and preferential attachment: Modelling and applications. *Journal of Complex Networks*, *9*(1). https://doi.org/10.1093/comnet/cnab008

Pizzuti, C., & Socievole, A. (2018). *Motif-Based Community Detection in Multiplex Networks*. https://doi.org/10.1007/978-3-319-72150-7_16

Rabb, N., Cowen, L., & de Ruiter, J. P. (2023). Investigating the effect of selective exposure, audience fragmentation, and echo-chambers on polarization in dynamic media ecosystems. *Applied Network Science*, *8*(1), 1–29. https://doi.org/10.1007/s41109-023-00601-3

Rafique, W., Khan, M., Sarwar, N., & Dou, W. (2019). SocioRank*: A community and role detection method in social networks. *Comput. Electr. Eng.*, *76*(100), 122–132. https://doi.org/10.1016/j.compeleceng.2019.03.010

Ramaciotti, P., Cassells, D., Vagena, Z., Cointet, J.-P., & Bailey, M. (2024). American politics in 3D: Measuring multidimensional issue alignment in social media using social graphs and text data. *Applied Network Science*, *9*(1), 1–32. https://doi.org/10.1007/s41109-023-00608-w

Rani, P., & Shokeen, J. (2021). A survey of tools for social network analysis. *International Journal of Web Engineering and Technology*, *16*(3). https://doi.org/10.1504/IJWET.2021.119879

Raviv, L., Meyer, A., & Lev-Ari, S. (2020). The role of social network structure in the emergence of linguistic structure. *Cognitive Science*, *44*(8). https://doi.org/10.1111/cogs.12876

Redner, S. (2017). Dynamics of Voter Models on Simple and Complex Networks. https://doi.org/10.48550/arXiv.1705.02249

Roller, R., & Schweitzer, F. (2021). A new theory of social roles in networks. *socarxiv*. https://doi.org/10.31235/osf.io/xkafb

Rossetti, G., & Cazabet, R. (2018). Community discovery in dynamic networks: A survey. *ACM computing surveys (CSUR)*, *51*(2).

Rossi, R. A., & Ahmed, N. K. (2015). Role Discovery in Networks. *IEEE Transactions on Knowledge and Data Engineering*, *27*(4), 1112–1131. https://doi.org/10.1109/TKDE.2014.2349913

Ruan, Z., Iñiguez, G., Karsai, M., & Kertész, J. (2015). Kinetics of Social Contagion. *Physical Review Letters*, *115*(21). https://doi.org/10.1103/PhysRevLett.115.218702

Russo, A., Miracula, V., & Picone, A. (2024). Topics evolution through multilayer networks; analysing 2m tweets from 2022 qatar fifa world cup. *arXiv*. https://arxiv.org/pdf/2401.12228v1

Ruths, D., & Pfeffer, J. (2014). Social media for large studies of behavior. *Science*, *346*(6213), 1063–1064. https://doi.org/10.1126/science.346.6213.1063

Saatchi, A. G., Pallotti, F., & Sullivan, P. (2023). Network approaches and interventions in healthcare settings: A systematic scoping review. *PloS One*, *18*(2). https://doi.org/10.1371/journal.pone.0282050

Saxena, A., & Reddy, H. (2021). Users roles identification on online crowdsourced Q&A platforms and encyclopedias: A survey. *Journal of Computational Social Science*, *5*. https://doi.org/10.1007/s42001-021-00125-9
Sayama, H. (2020). Extreme Ideas Emerging from Social Conformity and Homophily, 113–120. https://doi.org/10.1162/isal_a_00349
Shadrova, A. (2022). It May Be in the Structure, Not the Combinations: Graph Metrics as an Alternative to Statistical Measures in Corpus-Linguistic Research. *Graph Technologies in the Humanities*. https://ceur-ws.org/Vol-3110/paper12.pdf
Shao, T., Ieiri, Y., & Hishiyama, R. (2021). Discovering multiple clusters of sightseeing spots to improve tourist satisfaction using network motifs. https://doi.org/10.1587/transinf.2020EDP7258
Sherry, J. (2015). The Complexity Paradigm for Studying Human Communication: A Summary and Integration of Two Fields. *Review of Communication Research*, *3*, 22–65. https://doi.org/10.12840/issn.2255-4165.2015.03.01.007
Shevtsov, A., Oikonomidou, M., Antonakaki, D., Pratikakis, P., & Ioannidis, S. (2023). What Tweets and YouTube comments have in common? Sentiment and graph analysis on data related to US elections 2020. *PLOS ONE*, *18*(1). https://doi.org/10.1371/journal.pone.0270542
Şimşek, M., & Meyerhenke, H. (2020). Combined centrality measures for an improved characterization of influence spread in social networks. *Journal of Complex Networks*, *8*(1). https://doi.org/10.1093/comnet/cnz048
Singh, S. S., Srivastava, V., Kumar, A., Tiwari, S., Singh, D., & Lee, H.-N. (2023). Social Network Analysis: A Survey on Measure, Structure, Language Information Analysis, Privacy, and Applications. *ACM Trans. Asian Low-Resour. Lang. Inf. Process.*, *22*(5). https://doi.org/10.1145/3539732
Singh, S. S., Srivastva, D., Verma, M., & Singh, J. (2022). Influence maximization frameworks, performance, challenges and directions on social network: A theoretical study. *Journal of King Saud University - Computer and Information Sciences*, *34*(9), 7570–7603. https://doi.org/10.1016/j.jksuci.2021.08.009
Smith, N. R., Zivich, P. N., Frerichs, L. M., Moody, J., & Aiello, A. E. (2020). A guide for choosing community detection algorithms in social network studies: The question alignment approach. *American Journal of Preventive Medicine*, *59*(4), 597–605. https://doi.org/10.1016/j.amepre.2020.04.015
Spiro, E. S. (2020). Online Communication by Emergency Responders during Crisis Events. In *The Oxford Handbook of Networked Communication*. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780190460518.013.11
Spitz, A., & Gertz, M. (2018). Entity-Centric Topic Extraction and Exploration: A Network-Based Approach. *Advances in Information Retrieval*, 3–15. https://doi.org/10.1007/978-3-319-76941-7_1
Srour, A., Ould-Slimane, H., Mourad, A., Harmanani, H., & Jenainati, C. (2022). Joint theme and event based rating model for identifying relevant influencers on Twitter: COVID-19 case study. *Online Social Networks and Media*, *31*. https://doi.org/10.1016/j.osnem.2022.100226
Tanskanen, S.-K., Lehti, L., Lexander, K. V., Virtanen, M. T., & Xie, C. (2024). *Explorations in internet pragmatics: Intentionality, identity, and interpersonal interaction*. Brill. https://doi.org/10.1163/9789004694453
Tardelli, S., Nizzoli, L., Tesconi, M., Conti, M., Nakov, P., Martino, G. D. S., & Cresci, S. (2024). Temporal dynamics of coordinated online behavior: Stability, archetypes, and influence. *Proceedings of the National Academy of Sciences*, *121*(20). https://doi.org/10.1073/pnas.2307038121
Tian, Y., Liu, S., & Wang, J. (2024). A corpus study on the difference of turn-taking in online audio, online video, and face-to-face conversation. *Language and Speech*, *67*(3), 593–616. https://doi.org/10.1177/00238309231176768
Tsugawa, S., & Niida, S. (2021). Analyzing the Effects of Social Network Structure on the Growth and Survival of Online Communities in Reddit. *IEICE Transactions on Communications*, *E104.B*(7), 760–769. https://doi.org/10.1587/transcom.2020CQP0006
Unlu, A., Truong, S., Sawhney, N., & Tammi, T. (2024). Unveiling the Veiled Threat: The Impact of Bots on COVID-19 Health Communication. *Social Science Computer Review*. https://doi.org/10.1177/08944393241275641
Van Atteveldt, W., & Peng, T.-Q. (2018). When Communication Meets Computation: Opportunities, Challenges, and Pitfalls in Computational Communication Science. *Communication Methods and Measures*, *12*(2-3), 81–92. https://doi.org/10.1080/19312458.2018.1458084
Vega, D., & Magnani, M. (2018). Foundations of Temporal Text Networks. *Applied Network Science*, *3*(1). https://doi.org/10.1007/s41109-018-0082-3
Vega, D., & Magnani, M. (2023). Metrics for temporal text networks. In *Temporal network theory*. Springer International Publishing. https://doi.org/10.1007/978-3-031-30399-9_8
Vega, D., Magnani, M., Montesi, D., Meseguer, R., & Freitag, F. (2016). A new approach to role and position detection in networks. *Social Network Analysis and Mining*, *6*(1). https://doi.org/10.1007/s13278-016-0346-9
Vosoughi, S., Roy, D., & Aral, S. (2018). The spread of true and false news online. *Science*, *359*(6380). https://doi.org/10.1126/science.aap9559

Waldherr, A., Geise, S., & Katzenbach, C. (2019). Because technology matters: Theorizing interdependencies in computational communication science with actor–network theory. *International Journal of Communication*, *13*(0). https://ijoc.org/index.php/ijoc/article/view/10580

Wasserman, S., & Galaskiewicz, J. (1994). *Advances in Social Network Analysis: Research in the Social and Behavioral Sciences*. SAGE Publications. http://ebookcentral.proquest.com/lib/uu/detail.action?docID=996700

Wayback Machine. (2021). https://web.archive.org/web/20210410093613/

Williams, H. T., McMurray, J. R., Kurz, T., & Hugo Lambert, F. (2015). Network analysis reveals open forums and echo chambers in social media discussions of climate change. *Global Environmental Change*, *32*, 126–138. https://doi.org/10.1016/j.gloenvcha.2015.03.006

Wolfe, A. W. (2011). Anthropologist view of social network analysis and data mining. *Social Network Analysis and Mining*, *1*(1), 3–19. https://doi.org/10.1007/s13278-010-0014-4

Xie, L., Wu, Z., Xu, P., Li, W., Ma, X., & Li, Q. (2022). *RoleSeer: Understanding Informal Social Role Changes in MMORPGs via Visual Analytics*. https://doi.org/10.48550/arXiv.2210.10698

Xie, L., Natsev, A., Kender, J. R., Hill, M., & Smith, J. R. (2011). Visual memes in social media: Tracking real-world news in YouTube videos. *Proceedings of the 19th ACM international conference on Multimedia*, 53–62. https://doi.org/10.1145/2072298.2072307

Xu, R., Zhang, Q., & Tan, S. (2023). The Formation of Reciprocal Social Support in Online Support Groups: A Network Modeling Approach. *IEEE Transactions on Computational Social Systems*, *10*(6), 3370–3384. https://doi.org/10.1109/TCSS.2022.3197641

Yang, D., Kraut, R., Smith, T., Mayfield, E., & Jurafsky, D. (2019). Seekers, Providers, Welcomers, and Storytellers: Modeling Social Roles in Online Health Communities. *Proceedings of the SIGCHI conference on human factors in computing systems. CHI Conference*, *2019*. https://doi.org/10.1145/3290605.3300574

Yang, H.-X., & Yang, J. (2019). Cooperation percolation in spatial evolutionary games. *Europhysics Letters*, *124*(6). https://doi.org/10.1209/0295-5075/124/60005

Yang, X.-H., Xiong, Z., Ma, F., Chen, X., Ruan, Z., Jiang, P., & Xu, X. (2021). Identifying influential spreaders in complex networks based on network embedding and node local centrality. *Physica A: Statistical Mechanics and its Applications*, *573*. https://doi.org/10.1016/j.physa.2021.125971

Yang, Z., Algesheimer, R., & Tessone, C. J. (2016). A comparative analysis of community detection algorithms on artificial networks. *Scientific Reports*, *6*(1). https://doi.org/10.1038/srep30750

Yin, X., Wang, H., Yin, P., & Zhu, H. (2019). Agent-based opinion formation modeling in social network: A perspective of social psychology. *Physica A: Statistical Mechanics and its Applications*, *532*. https://doi.org/10.1016/j.physa.2019.121786

Yus, F. (2018). Identity-related issues in meme communication. *Internet Pragmatics*, *1*(1), 113–133. https://doi.org/10.1075/ip.00006.yus

Zeng, X., Li, J., Wang, L., & Wong, K.-F. (2022). Modeling Global and Local Interactions for Online Conversation Recommendation. *ACM Transactions on Information Systems*, *40*(3), 1–33. https://doi.org/10.1145/3473970

Zou, B., Wang, Y., Kwoh, C. K., & Cen, Y. (2023). Directed collaboration patterns in funded teams: A perspective of knowledge flow. *Inf. Process. Manage.*, *60*(2). https://doi.org/10.1016/j.ipm.2022.103237