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Review

Using Exponential Random Graph Models for Social Networks to Understand Meta-Communication in Digital Media

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Abstract: In recent years; digital media has garnered widespread interest from various domains. Despite advancements in the technology of digital media for globalized communication; disparities persist in user interaction patterns across different regions. These differences can be attributed to the presence of a control system, known as meta-communication, which shapes the coding of information based on social relationships. Meta-communication is formed in various social contexts, resulting in varying communication patterns among different groups. However, empirical research on the social processes that form meta-communication in digital media is scarce due to the challenges in quantifying meta-communication. This study aims to introduce exponential random graph models as a potential tool for analyzing meta-communication in digital media and to provide a preliminary understanding of its formation. The use of such models could prove valuable for researchers seeking to study meta-communication in digital media.

Keywords: exponential random graph models for social networks; meta-communication; digital media; social process; stochastic models

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1. Introduction and Research Problems

Digital media, defined as any form of media that utilizes digital technology for communication, has become a widely used tool for exchanging information (Jensen 2011). Its diverse functions allow for the exchange of both verbal and nonverbal information, which are both crucial natures of human communication. Research by Bateson (1973) has shown that face-to-face communication often includes nonverbal cues about the context in which the communication is taking place. These nonverbal cues, such as clothing, dialect, social identity, and body language, provide important information about the social environment and cultural norms that shape communication patterns (Cenni et al. 2020; Ekti 2022). This flow of information regarding the context of communication is referred to as meta-communication. Bateson (1973) has identified two ways in which meta-communication influences the exchange of information, including the codification of interaction and the influence of social relationships.

The coding of information, through means such as repetition, illustration, and rephrasing, determines the meaning of the information within specific contexts. For instance, Bateson (1973) discovered that individuals could assign the meaning of "tiger" to the word "cat" while playing a specific game. The use of coding to explain interactions within various contexts can facilitate comprehension and reduce communication costs.

On the aspect of social relationships, the nature and form of information conveyed between communicators are influenced by the social identities of the communicators and the type of relationship they share. For instance, the statement "don't be rude" may carry varying connotations and impacts depending on whether the communicators are co-workers, family members, friends, or business partners.

Meta-communication encompasses these two interdependent aspects that permeate the entire communication process. Social relationships play a role in shaping the ways in which information is codified, while the underlying principles of codification imply social relationships. The interplay between codification and social relationships is an ongoing and reciprocal relationship, shaped by cultural context. Different cultural contexts give rise to distinct forms of codification and social relationships, leading to varied communication patterns of different social groups (Huston and Burgess 1979).

The significance of meta-communication in shaping information is increasingly significant in the context of digital media. The global communication facilitated by digital media allows for the comparison of communication patterns between different social groups worldwide (Saka and Garoma 2019; Meier and Reinecke 2021). Studies (Ajzen 2011; Madden et al. 1992) have shown that people primarily use digital media to maintain existing social relationships, rather than creating new ones, indicating that meta-communication including codification and social relationships is mostly shaped by local experiences rather than the digital media itself (Ortega et al. 2020). However, the mechanisms by which different forms of meta-communication constitute information in digital media remain to be fully understood.

To study meta-communication in digital media, it is first necessary to define its components. Jensen (2011) proposed a preliminary typology of four main forms of meta-communication in digital media, rooted in Bateson's (1973) concept of meta-communication as a cybernetic mechanism for exchanging information. Jensen viewed meta-communication in digital media as encompassing the control of digital information bases, as well as the control of information content and timing, similar to information codification. In addition to Bateson's logic, Jensen also drew on Roland Barthes' (1973) distinction between connotation and denotation in language signs to define relationships between communication systems and users based on the control forms of digital information. These relationships can result in four main types of meta-communication in digital media: third-party communication, iterative communication, processed communication, and recommended communication.

Having defined the components of meta-communication in digital media, further research on its practices is necessary. Despite being introduced in the 1970s, meta-communication in digital media has not received sufficient attention in the field of digital media studies despite its growing importance. One of the reasons for this neglect is the challenge of quantifying meta-communication (Jensen 2012). The formation of meta-communication occurs in dynamic and localized social processes, and uncovering the underlying regularities requires extensive and potentially multidisciplinary efforts. As a result, meta-communication in digital media may be viewed as a hypothesis for some time.

Despite the difficulties in precisely defining meta-communication, a social network analysis method can estimate the distribution of various types of ties formed by meta-communication within a given social network. The formation of social ties between individuals is similar to the formation of meta-communication, as they are both established through interactions with information and relationships between actors (Marsden and Friedkin 1993). As a result, the structural features of meta-communication can also be studied through the examination of social ties. One method is to use exponential random graph models for social networks to simulate the structure of meta-communication (Yon et al. 2021). This modeling approach allows for the investigation of which types of meta-communication are more likely to occur in a particular social network based on statistical data from the network (Yamane 1973; Zhang and Pentina 2012; Caimo and Gollini 2020).

Furthermore, this modeling approach prioritizes the formation of diverse structures of interaction that can be represented in social networks. These structures are observable, therefore minimizing the impact of unobserved details and other social processes on the estimation of probability distributions. The accuracy of these estimations improves with an increase in observed data and parameters incorporated into the model (Stivala et al. 2020). This modeling approach can be adapted to various research requirements, enabling more empirical investigation into meta-communication structures within specific social networks.

2. The Significance of This Study

The utilization of exponential random graph models in the analysis of social networks offers the potential to enhance both academic and practical understanding of meta-communication in digital media.

In the aspect of academics, the dynamic and implicit nature of meta-communication has made it difficult to quantify in academic studies, leading to limited attention paid to this topic. However, with the rise of digital media and its role as a platform for communication among various social groups, the examination of meta-communication has become increasingly possible. The different types of meta-communication, including codifications and social relationships that govern information exchange, are particularly salient in digital media and are manifested in the formation of tie structures within specific social networks. These structures are generated by varying interaction patterns such as inward transmission ties and outward transmission ties, which have different implications of inward popularity and outward expansiveness. Through quantitative modeling, it is possible to evaluate the structural differences that indicate social choices and preferences regarding meta-communication within different social networks.

From a practical perspective, the application of exponential random graph models has the potential to deepen our understanding of meta-communication in digital media and the interactions between various social groups. These models can help uncover the structures of meta-communication on digital media and the ways in which localized social networks engage with global networks. This investigation could be valuable to those with interests in international business or global information dissemination. By creating robust localized models for meta-communication in social networks, it may also be possible to comprehend distinct information exchange patterns, leading to reduced communication costs across cultural contexts.

The subsequent sections of this paper provide an overview of the literature on four types of meta-communication and the utilization of exponential random graph models in the analysis of social networks. The objective of this literature review is to assess the feasibility of incorporating meta-communication into exponential random graph models, thereby enabling a more quantifiable approach to the study of meta-communication. The possible hypotheses will also be presented for discussion.

3. The Four Types of Meta-Communication

Meta-communication was first introduced as a concept in communication studies by Bateson (1973). Based on his observations of face-to-face conversations, Bateson (1973) recognized the existence of multiple levels of abstraction in human verbal communication, a phenomenon known as polysemy. For instance, when an angry person states they are not angry, they are sending a message that contradicts reality. However, the recipient of the message can respond in one of three ways: by directly challenging the statement, by complying with it, or by changing the subject of the conversation. The choice of how to interpret the message often depends on the relationship between the two individuals and the codification of interactions in specific contexts. This highlights the idea that human communication is a layered system, where information exchange is at the surface level but also has an underlying system including codification and social relationships that determines the interpretation of the information. Thus, in human communication, people not only exchange information but also the underlying system, which Bateson referred to as meta-communication (Bateson 1973; Jensen 2011; Hjelmslev 1963).

The meta-communication is shaped by local experiences and is internalized through daily interactions with family, friends, neighbors, coworkers, and in social groups and communities (Pettegrew and Day 2015). The more exposure to real-life practices, the more likely communication patterns will become ingrained habits, providing a foundation for understanding communication in similar contexts without the need for clarifying every message (Bateson 1973; Jensen 2011). Scholars such as Castells (2007), McQuail (2010), and Hofstede (2006) have noted that even in the age of globalization and digitalization, communication experiences remain rooted in local practices. People exhibit different behaviors in various online spaces, and these localized patterns persist because they are cultivated through daily interactions in local contexts. As a result, the integration of local experiences into global experiences is of great significance in digital media, particularly the presentation of unobserved social processes just as meta-communication.

Meta-communication is a complex phenomenon that encompasses both conscious and unconscious social processes, as well as both verbal and nonverbal communication. It can encode multiple levels of information, such as words, tones, gestures, and other signs, to enhance the communication process. In real-life situations, these signs are interwoven in the context of face-to-face communication, where they serve as carriers of information. Over time, the advancement of communication systems has expanded the capacity for multi-layered communication, starting from interpersonal communication to mass communication, and finally to networked communication in digital media. In digital media, the various affordances of previous communication methods have been combined to support multi-layered communication. However, it is important to note that the layered structure of communication is not a result of digital media but rather a fundamental aspect of human communication (Jensen 2011; Park and Pooley 2008).

Digital media is equipped with the most advanced communication technology, which supports multi-layered communication. According to scholars such as Jensen (2011), Berry (2012), and Hofstede (2006), the potential of meta-communication in digital media has yet to be fully realized. Meta-communication can facilitate our understanding of local and global communication patterns and the interaction between them in digital media. Bateson (1973) defined meta-communication as the control processes of digital information, including the codification of information and the relationships between communicators. Jensen (2012) further expanded on this concept by identifying four prototypes of meta-communication, including the codification and relationships of interaction patterns between systems and users in digital media regarding two types of digital information control: information base control and items and time of information control. The four concrete types of meta-communication are as follows:

Third-party communication, as defined in this form, refers to information that is completely controlled by the system. This information can be shared with various entities, such as marketers, advertisers, or government authorities. In Table 1, the intersection of third-party communication is the second type of meta-communication of iterative communication. Unlike third-party communication, iterative communication is user-controlled and encompasses various forms of interactive patterns between users, including synchronous and asynchronous interactions in the form of comments, messages, re-sends, likes, video conversations, and other user-generated interfaces using tools from collaborative open sources.

Table 1. Jensen's four prototypes of meta-communication in digital media.

	Control of Information Base	
Control of time and items selected	**System**	**User**
System	Third-party communication	Processed communication
User	Recommended communication	Iterative communication

From "How to do things with data: Meta-data, meta-media, and meta-communication," by K. B. Jensen (2012), *First Monday*, *18*(10), (accessed on 10 February 2022, https://doi:10.5210/fm.v18i10.4870).

The remaining two types of meta-communication are processed communication and recommended communication, which are opposite in nature. Processed communication involves the documentation and analysis of an individual user's patterns of information utilization for the purpose of market analysis and billing. On the other hand, recommended communication focuses on grouping users with similar interests and customizing information recommendations to these targeted user segments.

Jensen (2011) uses these four prototypes to illustrate the range of communication practices in digital media. Although this typology is preliminary (Jensen 2011), it provides a structural perspective to analyze the concept of meta-communication. Defining these four types would be the first step to quantitatively analyzing the concept of meta-communication in digital media; the operationalization of these four types would be the next step.

4. The Exponential Random Graph Models for Social Networks

Quantifying the concept of meta-communication aims to uncover the cybernetic mechanisms of meta-communication in digital media. Meta-communication is primarily constituted of codification and social interactions, both of which are influenced by social contexts and cultural backgrounds. Using the theory of planned behavior as an example, it is impossible to define all the factors that influence different interactions in different contexts, and there are ongoing attempts to incorporate more undefined factors into the original model, which results in inconsistent predictions. It is difficult to categorize all types of social relationships and codifications that determine human communication under various social circumstances and cultural backgrounds because these types could be entangled and dynamic. However, social networks are the common byproducts of all types of interaction between actors, which place emphasis on general structures of interactions, instead of the abstract and dynamic categories of the interaction. Thus, investigating social networks could be a practical and economical technique to quantify meta-communication; the quantification of meta-communication is necessary to evaluate the empirical differences that exist in the structures of the four types of meta-communication within social groups of interest, as these differences may not be revealed through qualitative definitions. Furthermore, the quantification of meta-communication provides a solid empirical foundation for future quantitative studies to contribute to the discussion.

Jensen's (2011) four types of meta-communication encompass the interactive actions and relationships between users and systems. For the purpose of quantification, social network analysis is of significant importance as it views social ties as research objects, which are formed by the interactive actions and relationships between actors, similar to the mechanism of meta-communication (Granovetter 1973; Wasserman and Robins 2005; Wasserman and Faust 1994). Actors can refer to individuals, as well as collective units such as organizations and digital platforms. Social network analysis focuses on the underlying structures of interaction, similar to meta-communication. It has developed a set of statistical methods for investigating structural features based on various social network graphs (Cochran 1977; Knoke and Yang 2019), and exponential random graph models could be an ideal tool for quantifying meta-communication.

Exponential random graph models are a series of stochastic models that can estimate the probability distribution of all possible ties in social networks existing in a set of actors (Leifeld and Cranmer 2019), also known as p* models in the field of social network analysis (Anderson et al. 1999). The assumptions about the probabilities of ties arising between actors in observed social networks rely on the existence of other similar relationships in a given social network. For example, in a network of n actors, a friendship tie may have a higher chance to exist between actor A and actor B while other ties are more likely to be friendship ties. When friendship ties are not detected in this network, the relationship tie between A and B is less likely to occur (Watts 1999). The logic behind exponential random graph models can be further explained in the following general model:

$$Pr(Y = y) = (\frac{1}{k})exp\left\{\sum_{A}\eta_A g_A(y)\right\} \tag{1}$$

In Equation (1), Y represents all possible ties within a given social network with a fixed set of n actors; for example, in a social network with 5 actors, the sum of all possible ties existing among 5 actors is 10, which is calculated through the formula of $C^5{}_2 = 5!/(2! \times (5-2)!) = 120/12 = 10$. While y represents the actually observed ties in Y, the density of ties, or $g_A(y)$, is the ratio of observed ties to all possible ties in the exponential random graph model. The term A refers to a configuration or substructure that exists in Y; in other words, A refers to the research structural units in the specified social network, as shown in Figure 1. Figure 1 illustrates how two actors and a tie between them could be viewed as a research unit called an edge, how a structural unit of three actors could be a two-star unit or a triangle unit, and how a three-star unit could be made up of three actors surrounding one center actor.

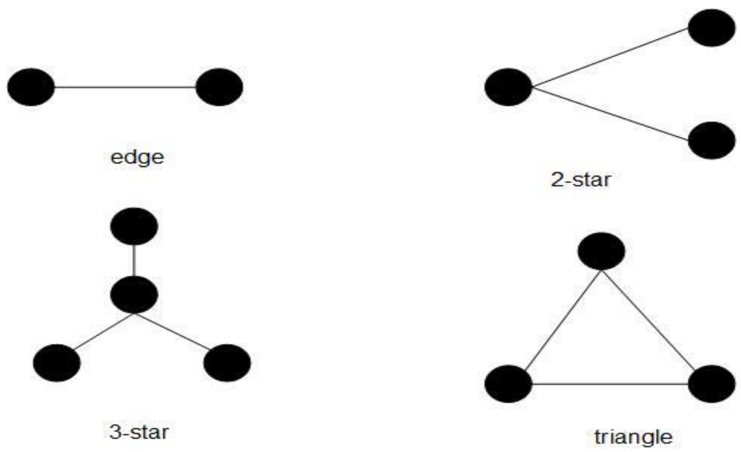


Figure 1. Configurations in a social network.

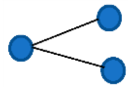
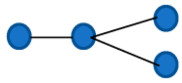
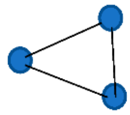
The η_A indicates the parameter associated with the observed configuration A, and parameters for different configurations indicate the different impacts of these configurations in a certain social network. For example, the three-star configuration is unlikely to occur and has no consequences for this social network if the value of the corresponding parameter is 0. It is possible that the three-star configuration has been seen and has an impact on this social network if the parameter is bigger than zero. The maximum likelihood estimation approach, which is based on the statistics of observed configurations, namely the number of observed configurations in the social network, presented by $g_A(y)$ in Equation (1), could estimate the parameters corresponding to configurations. The normalizing quantity k ensures that the model is a valid probability distribution. To involve different configurations and their corresponding parameters in the model, Equation (1) could also be presented in the form of Equation (2).

$$Pr(Y = y) = (\frac{1}{k})exp(\theta L(y) + \sigma_2 S_2(y) + \sigma_3 S_3(y) + \tau T(y)) \quad (2)$$

Equation (2) shows that $L(y)$ represents the observed number of edges in the social network, $S_2(y)$ represents the observed number of two-star configurations, $S_3(y)$ represents the observed number of three-star configurations, and $T(y)$ represents the observed number of triangle configurations. Statistics of configurations and the normalizing quantity of k can be used to determine the parameters of θ, σ_2, σ_3, and τ. PNet, StOCNET, and R are three examples of analytic software; they are all very user-friendly and useful for social network analysis.

A short example of the parameter estimation of Equation (2) is presented in Table 2. This set of data presents a non-directed social network constituted of 38 students, the density of this social network is 0.09, and then the parameters of four kinds of configurations are estimated.

Table 2. The parameter estimation of configurations in the social network.

Parameter	Configuration	Estimate (Standard Error)
θ		−3.116 (1.36)
σ_2		0.055 (1.84)
σ_3		−0.022 (0.13)
τ		1.057 (8.4)

As shown in Table 2, the dyadic edge ties and centralized three-star ties have a minimal probability of having an impact on this social network, as the negative parameters show that configurations of the edge and three-star are not likely to exist in this social network. On the other hand, positive parameters suggest that two-star and triangle configurations are more likely to be seen in this social network and will influence how people connect to one another. Triangle configurations could represent the propensity to create cliques or small groups in this social network, while two-star configurations could represent the tendency to have more than one contact.

With the exponential random graph models, the quantification of meta-communication can be approached through the examination of the four distinct types of meta-communication as sub-structures in social networks. Researchers can investigate the presence of these four types within social networks, specifically focusing on the formation of specific types of meta-communication ties. Additionally, researchers can estimate the parameters in models based on data collected from social networks to gain insights into the types of ties, such as single ties, reciprocity ties, or triangle ties, that exist within a particular type of meta-communication.

In the modeling process, researchers can make assumptions about the formation of different types of ties based on the observed data in specific social networks. The choice of exponential random graph models is contingent upon the researchers' academic and practical goals. These models not only consider the formation of various tie types but also the relationships between them. The more detailed the data collected from social networks, the better-suited the chosen models will be. The subsequent section will introduce the primary assumptions of the modeling process.

4.1. The Assumptions about Ties' Independence from Each Other

Regarding meta-communication, if researchers determine that the ties of the four types of meta-communication in a specific social network are independent of each other, meaning that the four configurations in the network do not have a mutual impact, the parameters of these configurations can be set as equal, represented by θ. For the purposes of representation, 1 is used to indicate systems, and 2 represents users. Ties between systems can be assigned the parameter θ_{11}, ties between users can be assigned θ_{22}, ties from systems to users can be assigned θ_{12}, and ties from users to systems can be assigned θ_{21}. The ties formed with θ_{22} can be considered as third-party communication, those formed with θ_{11} can be seen as iterative communication, θ_{12} can represent recommended communication, and θ_{21} can represent processed communication. Therefore, the model can be expressed as follows:

$$Pr(Y = y) = (\frac{1}{k})exp(\theta_{11}L_{11}(y) + \theta_{12}L_{12}(y) + \theta_{21}L_{21}(y) + \theta_{22}L_{22}(y)) \quad (3)$$

In Equation (3), $L_{11}(y)$ is equal to $\sum_{1,1} y_{1,1}$, which means the summation of third-party communication ties observed in the social network of y. θ_{11} is the parameter associated with the probability of observing third-party communication ties, while the other configurations in the model are estimated in a similar manner. This model is considered to be the simplest as the configurations in the social network are assumed to be independent, as noted by Contractor et al. (2006) and Moreno and Jennings (1938), and the probabilities of each configuration are assumed to be equal, meaning that all four types of meta-communication have an equal chance of being observed within the given social network. The results of the estimation are presented in Table 3.

Table 3. The independent assumption of meta-communication using the exponential random graph model.

Configuration	Third-Party Communication (System to System)	Recommended Communication (System to Users)	Processed Communication (Users to System)	Iterative Communication (Users to Users)
Edge	θ_{11}	θ_{12}	θ_{21}	θ_{22}
2-star	θ_{11}	θ_{12}	θ_{21}	θ_{22}
3-star	θ_{11}	θ_{12}	θ_{21}	θ_{22}
Triangle	θ_{11}	θ_{12}	θ_{21}	θ_{22}
Other configurations	θ_{11}	θ_{12}	θ_{21}	θ_{22}

However, in real-world social processes, equal probabilities may not be realistic due to variations in interactive patterns, social preferences, and relationships established in different cultural settings among individuals within different social networks. The different configurations in social networks can interact and influence each other, leading to variations in the parameters among configurations. To address these complexities, the exponential random graph models include more advanced models that enable researchers to assume different probability distributions for the configurations.

4.2. The Assumptions about Ties' Dependence on Each Other

In other exponential random graph models, the Markov random graph model assumes the occurrence of given ties relies on the existence of other ties, they often share common actors (Frank and Strauss 1986; Robins et al. 2007). For example, the occurrence of a tie between actor i and actor j depends on the tie between actor j and actor r. It is a normal situation concerning intimate relationships: whether two people choose to date or not depends on whether they already have intimate relationships with other people. The dependence of ties could be represented by the parameters of configurations, just as Equation (2) shows. When it comes to meta-communication, the assumption could be that the occurrence of third-party communication ties is contingent on tie formation in processed communication, recommended communication, and iterative communication.

In Equation (2), $L(y)$ represents the number of edge ties, $S_2(y)$ denotes the number of two-star ties, $S_3(y)$ represents the number of three-star ties with three paths, and $T(y)$ is the number of ties in the form of triangle paths. There is a hierarchical order present, with single paths being of a lower order and triangle paths being of a higher order. For instance, the existence of a triangle tie automatically implies the presence of two paths and single ties within its structure. The dependent relationships between these configurations are established through shared actors, leading to the overlapping of these hierarchical configurations. The dependent assumptions could be presented by different parameters, which indicate the dependent relationships among configurations. The basic logic is shown in Table 4.

Table 4. The dependent assumption of meta-communication using the exponential random graph model.

Configuration	Third-Party Communication (System to System)	Recommended Communication (System to Users)	Processed Communication (Users to System)	Iterative Communication (Users to Users)
Edge	θ_{11}	θ_{12}	θ_{21}	θ_{22}
2-star	σ_{11}	σ_{12}	σ_{21}	σ_{22}
3-star	σ_{11}	σ_{12}	σ_{21}	σ_{22}
Triangle	τ_{11}	τ_{12}	τ_{21}	τ_{22}
Other configurations	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}

In other circumstances, there could also be dependent relationships that are not established through shared actors or overlapping but rather through third-party links; in meta-communication, ties between users and users could be dependent on ties between systems and systems. Users may establish connections depending on the relationship between social media and enterprise, for instance. In such case, digital platforms could facilitate the mutual influence between these two types of ties. Moreover, spatiotemporal factors or the attributes of the factors could also be used to build the dependent relationships (Pattison and Robins 2002).

The choice of models, whether dependent or independent assumptions, is contingent upon the research objectives and the collected data. The basic models of dependent or independent assumptions can be augmented to incorporate the features of configurations, relationships between configurations, and attributes of actors, as long as the selected models are capable of fitting the observed data and fulfilling the research goals.

5. Possible Hypotheses Regarding Meta-Communication in Digital Media

The exponential random graph models, as discussed in this paper, provide a means to examine the structural features of interactions and relationships and can serve as a powerful quantification method for exploring the structural features of meta-communication. With regard to studies on various exponential random graph models, the following hypotheses regarding the four types of meta-communication could be proposed. These include assumption about the occurrence of ties, which is H1, assumption of H2 about the dependencies between ties, and assumption of H3 about the influence of actor attributes on tie occurrence.

H1. *The ties of third-party/iterative/processed/recommended communication are more likely to occur in the given social network.*

H2. *The ties of third-party/iterative/processed/recommended communication are dependent on each other in the given social network.*

H3. *The attributes of actors in third-party/iterative/processed/recommended communication impact possible ties involving actors.*

In actual studies, the assumptions and applications of exponential random graph models can be far more complex and diverse than these primary hypotheses. Nevertheless, the fundamental logic of the probability distribution in exponential random graph models remains consistent. This enables us to investigate more possibilities in constructing meta-communication models in digital media that are firmly rooted in dynamic and localized social experiences. The meta-communication that shapes our diverse communication patterns in digital media could be further illuminated through future studies.

6. Conclusions

In this conceptual paper, the concept of meta-communication has been introduced. Meta-communication refers to the underlying mechanisms that shape information exchange and communication patterns, encompassing two interdependent aspects: codification and social relationships. These aspects are shaped by diverse spatiotemporal settings, resulting in unique communication patterns in digital media that are rooted in local experiences. In digital media, users and systems play a key role in managing digital information, which contributes to shaping meta-communication patterns. Jensen (2011) categorizes these patterns into four main types of meta-communication in digital media: third-party communication, iterative communication, processed communication, and recommended communication.

The four types of meta-communication in digital media depict the interactions between users, systems, and information. To gain a better understanding of these interactions, it is necessary to conduct quantifiable and empirical studies of meta-communication. The exponential random graph models offer a statistical approach to examining the complex and diverse processes of meta-communication. These models aim to determine the probability distributions of different types of meta-communication in specific social networks in digital media. By simulating real-world data, researchers can generate hypotheses about the social processes that shape the four types of meta-communication in digital media.

The concept of meta-communication has yet to reach its full potential in communication studies, largely due to the challenge of capturing the regularities underlying complex communication patterns. However, digital media has provided ample opportunities for the investigation of meta-communication, and the exponential random graph models have the ability to quantify the dynamic formation of its structural features. This conceptual paper presents an initial exploration of the integration of the concept of meta-communication with the method of exponential random graph models, with the aim of stimulating further empirical studies on meta-communication in digital media in the future.

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