International Journal of Communication 17(2023), 6250–6268 1932–8036/20230005

Communication Network Characteristics of the Mass Entrepreneurship and Innovation Policy on Social Media: A Social Network Analysis

ZENGLEI YUE♦
Harbin Institute of Technology, China
Heilongjiang Institute of Science and Technology Information, China

GUANG YU
Harbin Institute of Technology, China

JING SHAN
GUANGWU LIU
LIE CHEN
Heilongjiang Institute of Science and Technology Information, China

DONGHUI YANG
Southeast University, China

Policy communication network structure can be taken as a result and as a target of policy communication on social media. This study explores the communication network of the Mass Entrepreneurship and Innovation policy on social media, using social network analysis, to investigate the relationships that were constructed as a result of policy-related interactions, through visual and quantitative means. The results revealed that the entire network structure comprised a relatively concentrated interactive group, some numerous scattered subgroups, and independent nodes, with policy audiences playing an integral and crucial role. In the core network structure, different user nodes had differential influences in the policy network structure. Nodes associated with government sectors and media played relatively important roles in expanding the scope of communication and displayed more advantages in deepening interaction. These findings have implications for the effective communication of policies. Measures should be adopted to avoid or minimize negative impacts in the policy communication on social media.

Zenglei Yue: yuezenglei@stu.hit.edu.cn
Guang Yu (corresponding author): yug@hit.edu.cn
Jing Shan: 543650439@qq.com
Guangwu Liu: 34809716@qq.com
Lie Chen: 106038333@qq.com
Donghui Yang: dhyang@seu.edu.cn
Date submitted: 2022-10-16

Keywords: policy communication network, social media, Mass Entrepreneurship and Innovation policy, social network analysis, network structure

The Internet has evolved into a ubiquitous and indispensable digital environment (Kozyreva, Lewandowsky, & Hertwig, 2020). In the field of politics and policy, the Internet enables unprecedented levels of political and policy communication among public officials, organizations, and citizens (Rethemeyer & Hatmaker, 2007). The advent of social media has revolutionized the way people access and use information, expediting the dissemination and exchange of information (Cahyani, 2019). Social media establishes a nexus of policy networks on the Internet, providing individuals with greater global connectivity and interaction, fostering conversations on specific areas of concern, such as social issues (Charalambous, 2019; Zhang & Counts, 2015). Social media has become the primary avenue for public engagement in matters of public affairs and politics, with opinion leaders shaping political opinions through the dissemination of information and debates (Amjad, Saeed, Ali, & Awais, 2020). It has gradually emerged as a platform to promote government transparency, communication, and public engagement (Bou-Karroum et al., 2017), while serving as a crucial channel for policy dissemination. Moreover, social media is instrumental in understanding the information needs of the public, sharing vital information, and reshaping policy-making processes, which are essential for local governments to develop effective crisis management strategies (Wang & Wei, 2019).

Social network analysis (SNA) is a method that allows for the description and measurement of social structures by mapping relationships between individuals (Farine & Whitehead, 2015). It provides visual representations of complex relationships within networks (Malathi & Radha, 2016) and helps reveal important aspects such as resource exchange, information transmission, political power dynamics, boundary penetration, and emotional attachments within policy networks (Knoke, 2018). In the context of policy communication research on social media, SNA offers valuable insights into the relationships and roles involved in social interactions (Davies, 2009). Identifying influential nodes in the policy communication structure on social media is crucial for achieving efficient information diffusion (Kumar & Panda, 2020). Therefore, identifying these influential nodes becomes essential to effectively disseminate policy information throughout the network (Zhang, Li, & Gan, 2021), which can be addressed by SNA.

In this study, the research questions are divided into two aspects: (i) How to construct an implicit network of policy communication on social media platforms? (ii) How to use SNA to identify important nodes in the policy dissemination network on social media platforms?

Literature Review

Policy Communication

Policy communication research aims to investigate how governments, policy makers, and stakeholders effectively disseminate policy information and shape public attitudes and behaviors (Clarke & Margetts, 2014). Traditional media play a vital role in policy communication, including news coverage and televised debates, given their significant influence on shaping public attention and ideological perspectives (Mathias, Hans-Bernd, & Friedrich, 1991). In addition to stakeholders and nongovernmental organizations as primary participants in policy processes, public plays a crucial role in policy formulation, dissemination, and implementation (Stolle, Hooghe, & Micheletti, 2005). Internet has not only transformed and enriched policy communication channels but also revolutionized the patterns of political discourse and engagement (Lilleker, Jackson, & Thorsen, 2016). With the rise of social media, policy communication research has shifted its focus to exploring the role of social media in dissemination of policy information, public engagement, and policy influence. Social media platforms provide an open and interactive space that allows policy makers to engage in direct communication with the public, fostering public participation and discussion on policy topics (Himelboim, Smith, & Shneiderman, 2013). Opinion leaders and stakeholders can effectively use social media platforms to disseminate their policy agendas, thereby influencing public opinion and the policy decision-making process (Jungherr, 2016).

SNA in Policy Research

In the realm of policy studies, scholars have depicted the policy-making process as an actor network, using SNA to examine and analyze the relationships between actors and the network structures within the policy-making process. Drew, Aggleton, Chalmers, and Wood (2011) argued that employing SNA to evaluate complex policy networks is valuable for documenting and analyzing the interrelationships between individuals and organizations. They emphasized the potential for identifying gaps and areas for development within these networks. Vanderelst (2015) underscored the significance of SNA as a valuable tool in policy research and used it to assess the national and international collaboration among German researchers and research institutions in neglected tropical diseases. McIntyre, Jessiman-Perreault, Mah, and Godley (2018) visualized the networks of food insecurity policy actors in Canada and found that while networks of Canadian food insecurity policy actors exist, they are limited in scope and reach, with a scarcity of policy entrepreneurs from political, private, or governmental domains. Kalantari, Montazer, and Ghazinoory (2021) analyzed the science and technology policy-making network in Iran using SNA, with a focus on the most influential science and technology policy-making institutions in the country and the interactions between them from a network perspective.

However, based on our previous research, only few studies have employed SNA to analyze the network structure and characteristics of policy communication on social media.

Mass Entrepreneurship and Innovation Policy

Innovation has become the centerpiece of development strategies across countries worldwide (Stankevice, 2014). As a developing country, China issued the *Opinions on several policies and measures to vigorously promote mass entrepreneurship and innovation* (i.e., the Mass Entrepreneurship and Innovation policy) by the State Council in June 2015 to promote entrepreneurship and innovation. This policy aims to modernize entrepreneurship and innovation, thereby fostering a powerful new driving force for economic and social development. After the policy was officially released and implemented, several media sources on the Internet reprinted the full text of the policy and published numerous reports, which triggered widespread attention a heated debate (Huang, Zhao, Liu, Wu, & Li, 2018). Up to the end of July 2015, the total amount of the policy information disseminated on the Internet exceeded 2.71 million items, and the amount of uploaded and broadcast on social media reached 1.66 million items (Wang, Tong, & Yi, 2019). In recent years, discussions on policy topics are still accumulating on social media.

In summary, this study examines the communication network structure of the Mass Entrepreneurship and Innovation policy on social media platforms. The objective is to use SNA to providing a clear description and visualization of the relationships within the communication process. The findings of this study are expected to assist policy makers in developing effective policy communication strategies. The next section outlines the research methodology employed, followed by a detailed description of the communication network structure. Subsequently, the results are presented and discussed, leading to the final conclusion.

Methodology

Definitions

Nodes and Edges

We used SNA to study the policy communication network on social media. The network presented by the graph is composed of nodes and edges. These nodes are the actors engaging in policy formulation and implementation, and the edges refer to the relationships among the actors. However, unlike other social networks, nodes and edges reflect the unique attributes of social media. Primarily, actors from different backgrounds or identities can participate in this network directly without functional constraints. First, in this study, we define a user ID on social media as a node, regardless of identity. For example, government sectors, organizations, groups, media, or individuals are all policy actors, and they can be regarded as nodes in this network as long as they participate in the interaction and discussion of policy topics. Second, the relationship between social media users arises from the interaction or connection between them. Social media platforms provide users with many functions to establish connections and interact with other users. Comments, forwarding, and giving likes are the basic forms of direct connection between users. The relationships realized by these functions are defined as edges. Third, to explicitly define the research scope, we need to give a boundary to this network. This network includes all the nodes that enter the discussion of policy topics and the resultant edges. However, the links established between these nodes (those entering the discussion) that are not related to policy topics are not included in the policy communication network; they belong to the broader network relationship between nodes.

Policy Communication Network

Interactivity is one of the main characteristics of social media. Users can exchange information, opinions, and views with other users through interactive actions. In the interaction based on policy topics, users can freely share policy information and express their understanding toward policy content. The more interactive their behaviors, the more edges are formed between user nodes. These nodes and edges together construct an interactive network based on policy. In this interactive network, policy information flows from one node to another along the edge. Policy information gradually spreads on social media along this interactive network. Therefore, the interactive network formed by user nodes based on policies is the policy communication network. In this policy communication network, the nodes and paths (edges) of policy communication are formed, and the views of users on policy are absorbed in the process of policy communication. This highlights the need to analyze the network structure of policy communication on social media, so as to better understand the characteristics and effects of policy communication on social media. Another significant point is that individual users play a very important role in the process of policy communication on social media. They can communicate and discuss directly with government sectors, organizations, groups, or media and establish a connection without any intermediaries. Because there is no difference at the user node level, they are all regarded as single nodes. The only difference is that there may be innate connections among government sectors, organizations, groups, and media, and these relationships are likely to be closely related to policy topics.

Policy Selection

"Mass entrepreneurship and innovation" comes from Premier Li Keqiang's speech at the summer Davos Forum in September 2014 (Keqiang, 2014, p. 3). Li Keqiang proposed to set off a new wave of "mass entrepreneurship" and "grassroots entrepreneurship" on a land of 9.6 million square kilometers, promoting a new trend of "mass innovation" and "everyone innovation." Since then, he has frequently explained this keyword in the first World Internet Conference, the executive meeting of the State Council and the 2015 government work report. In June 2015, the State Council issued the Mass Entrepreneurship and Innovation policy to promote entrepreneurship and innovation. The purpose of this policy is to make entrepreneurship and innovation up to speed with the trend of the times and to nurture a powerful new driving force for economic and social development. In September 2018, the State Council issued the *Opinions on Promoting the High-quality Development of Innovation and Entrepreneurship and Creating an Upgraded Version of "Mass Entrepreneurship and Innovation"* (State Council of The People's Republic of China, 2018). We choose this policy as the research object of policy communication on social media because it affects all aspects of social innovation and development, and it relates to more policy audiences, especially the policy audiences at the individual level. The introduction of the policy resulted in a heated discussion on social media. To implement this policy, the state, ministries, and local governments have issued a number of policies and measures to promote innovation and entrepreneurship. These policies have become a set of policy systems, and they continue influencing innovation and entrepreneurship practice. Therefore, this policy is a suitable research object for this study.

Data Collection and Preprocessing

We chose Sina Weibo, which is one of the biggest Chinese microblogging platforms, for data collection. This was a pragmatic choice because Sina Weibo provides greater accessibility to research data compared with other social media platforms, which restrict data accessibility because of privacy concerns. Moreover, we can easily obtain a user's authentication identity, which can be used to classify and analyze the audiences. Most importantly, on Sina Weibo, users can openly interact, discuss, and transmit information. These data are the key to this study and they are readily available.

We collected Weibo data from June 2015 until May 2016, which represents the one-year period after the implementation of Mass Entrepreneurship and Innovation policy. We used this data set to construct the communication interaction network of the policy and elucidate the policy communication structure on social media. Sina Weibo provides the topic discussion function, and users can participate in the topic discussion of their interest as long as they use the symbol # before and after the relevant keywords or phrases. For this reason, we searched the data using the keywords with ##. "#Mass Entrepreneurship and Innovation Policy#" and "#Double Creation#" were the most frequent keywords in the policy text and abbreviation of policy. We have also considered the particularity of Chinese expressions and have collected topics based on keywords with links such as spaces, colons, and commas in the middle. Thereafter, we performed manual screening, excluding the following items: if they were posted repeatedly, if they were advertisements or commercial information, or if they were irrelevant to the policy. Finally, 7,187 items were used, including 1,512 posts, 1,908 comments, 2,922 instances of forwarding, and 845 likes.

SNA

In network analysis, the interaction of policy communication network can be quantified by degree, which refers to the interaction frequency. A node gets 1 out-degree if it initiates an interaction toward another node and 1 in-degree if it accepts one from others. For example, if an audience member A comments on B's post, then the output degree of A and the input degree of B is 1 simultaneously. The total degree of each node is then calculated, that is, the sum of out-degree and in-degree, which represents the total interaction frequency of one node. We can identify key nodes by calculating their degree, as we believe the higher the degree, the higher the importance of the node in the network structure. This identification enhances the analysis of the behavior patterns of the entire network, particularly the behavior patterns of each node and connections in the network, and reveals the high-value nodes from the perspective of network measurement. In addition, we compare some key indicators to conduct a further analysis.

The SNA process in this study follows these steps: First, we crawled the policy topic data on Sina Weibo and conducted preprocessing. Second, we constructed an interaction matrix and explored the interactive network for the policy topic using Pajek (a software for analysis and visualization of large networks). Third, we analyzed and explained the characteristics of the policy communication network according to key indicators.

Clustering Coefficient

Clustering coefficient is used to indicate the transitivity of a graph: the proportion of all closed dual paths in the network. The Watts–Strogatz clustering coefficient is calculated by averaging the clustering coefficients of all nodes with a degree of at least 2. Value C_i denotes the clustering coefficient, and $\bar{C}$ denotes the Watts–Strogatz clustering coefficient; $\lambda(v)$ is the number of subgraphs with three edges and three nodes in the network, and v is one of the nodes, while $\tau(v)$ is the number of triples with three nodes connected by two or three undirected edges.

$$C_i = \frac{\lambda(v)}{\tau(v)}$$

$$\bar{C} = \frac{1}{n}\sum_{i=1}^{n} C_i$$

Degree Centrality

Degree centrality refers to the number of connections (edges) a vertex has to other vertices. In the network, the greater the degree of a node, the higher the degree centrality of the node, which means that the node is more important in the network. We use DC to represent the degree centrality of a node, where n is the number of nodes and N_{degree} indicates the degree of the node, that is the sum of in-degree and out-degree. DC is defined as follows:

$$DC = \frac{N_{\mathrm{degree}}}{n-1}$$

Betweenness Centrality

Betweenness centrality is an index that describes the importance of a node by the number of shortest paths through a node. It measures the extent to which a node is located in the middle of other node pairs in the network structure so that it plays an important intermediary role. We use BC to represent the between centrality of a node v, where d_{ij} is the number of shortest paths from i to j, and $d_{ij}(v)$ indicates the number of nodes in the shortest path from i to j that pass through node v. BC is shown in the following formula:

$$BC(v) = \sum \frac{d_{ij}(v)}{d_{ij}}$$

Closeness Centrality

Closeness centrality reflects the proximity between a certain node and other nodes in the network structure. If a node is close to other nodes, it does not need to rely on other nodes when transmitting information, which indicates that this node is important. We take CC_i as the closeness centrality of node i; CC_i is based on average shortest path length d_{ij}. Value CC_i is shown in the following formula:

$$CC_i = \frac{1}{d_i} = \frac{n-1}{\sum_{j\neq i} d_{ij}}$$

Analysis and Results

Interactive Network Structure

Based on the data set, we constructed an interaction matrix of 2,979* 2,979 and explored the interactive network of the policy topic using Pajek. Figure 1 presents the entire interactive network structure.

There were a relatively concentrated interactive group (inside the black dotted line) and numerous scattered subgroups. There are also some independent nodes without any relations with others.

Figure 1. The entire interactive network structure of the Mass Entrepreneurship and Innovation policy topic by the end of the first year.

For the concentrated interactive group, these nodes indicated the interaction among users who participated in the policy topic. Some interactions are onetime while others are repeated. There were many interactions and deeper communication on the policy topic, which can better reflect the public's thinking and feedback on the policy. Their interactive behavior greatly promotes the communication of policy information in the interactive network structure. In this way, we will conduct deeper research on the concentrated interactive group later.

For the numerous scattered subgroups, we found that unlike concentrated interactive group, almost all subgroups have a core node. The core nodes had point-to-point relationships with other nodes. In other words, there is no connection between other nodes. Consequently, the core nodes had become the central nodes of each subgroup because they had received more attention from other users. Therefore, we thought that these core nodes helped to expand the dissemination of policy information in the interactive network, but there was a lack of deep interaction among members of such subgroups.

Furthermore, we also found that there were some independent nodes in the entire interactive network structure. Those independent nodes represented those users who posted an item under the policy topic, but did not produce any interaction with other users. These users only randomly participated in the discussion of the policy topics, but did not communicate with other users. In other words, they did not promote the communication of the policy information in this structure. However, if considered in the whole social media network, they have made certain contributions to policy communication.

Core Network Structure

As mentioned above, there were many interactions and a deeper communication on the policy topic in the concentrated interactive group. To examine how the interactive behavior promotes the communication of policy information in the network structure, we conducted a deeper analysis of the concentrated interactive group.

First, we separated the concentrated interactive group from other subgroups and independent nodes. Thereafter, in the remaining data sets, we removed the nodes with degree = 1 (in-degree = 1 or out-degree = 1) and their interaction with other nodes. This was done to simplify the core network structure, only retaining the more important relationships and nodes with multiple interactions. Additionally, it reduces the impact of interactions that may occur randomly. We believe that if a user wants to participate in the topic discussion in depth, they are more likely to continuously pay attention to and trigger the interaction behavior many times. After these processes, the core network matrix was 210*210; the core network structure of policy topics we obtained is shown in Figure 2.

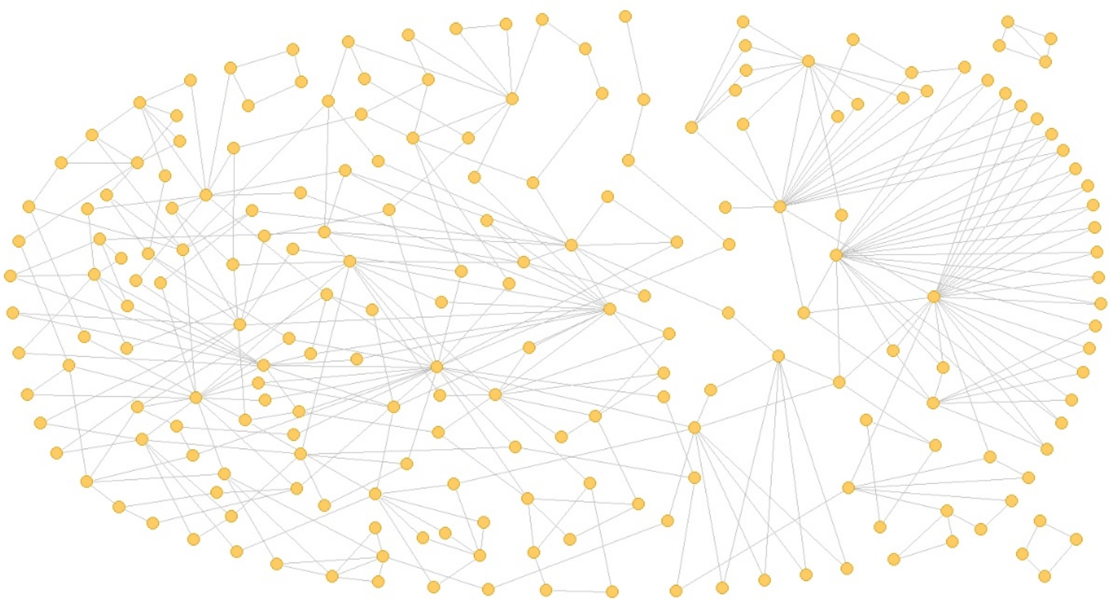

Figure 2. The core network structure of the Mass Entrepreneurship and Innovation policy topic by the end of the first year.

We found that there were two separated subgroups in the core network structure as a result of moving the nodes of a single relationship and their edges. However, since their degree is still higher than that of other nodes, we retained them in the core network structure.

To further analyze these nodes and relationships, we performed the following steps for processing: First, we set the size of nodes according to the degree of nodes. Second, we introduced directed edges according to the triggering and receiving of interactive actions. Third, we numbered each node to facilitate description and analysis. Finally, we obtained the processed core structure shown in Figure 3.

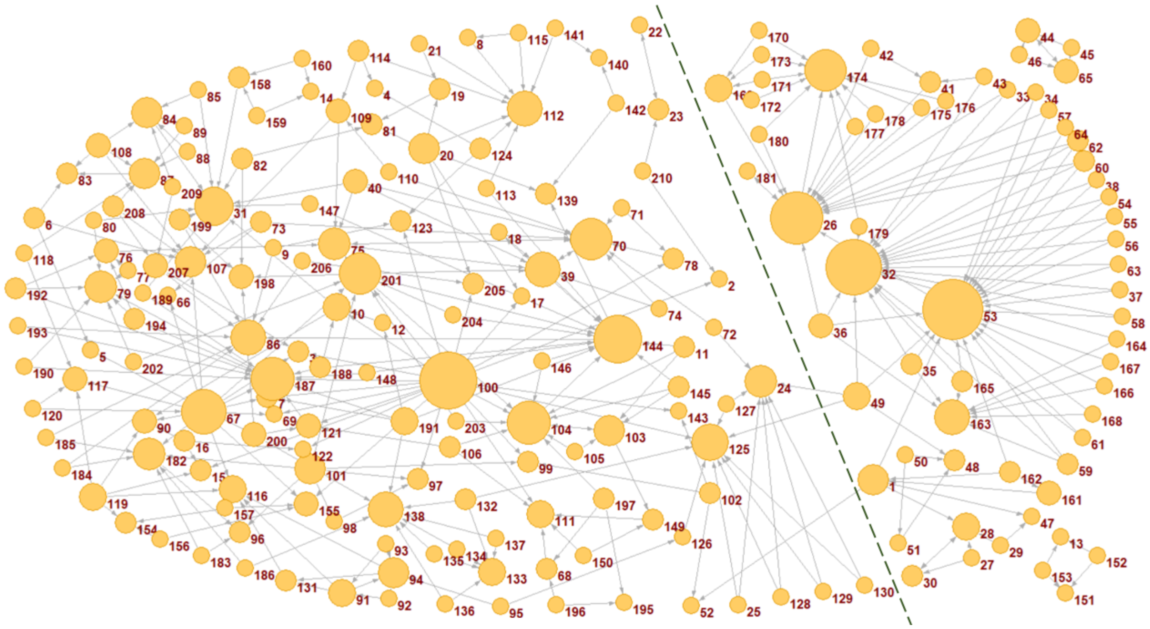

Figure 3. The processed core network structure of the Mass Entrepreneurship and Innovation policy topic by the end of the first year.

We calculated the clustering coefficients of both the entire network and core network. Table 1 reports the results, which revealed that nodes in the core network structure converged more closely than those in the entire network structure. This means that users in the core network structure had built closer relations based on the policy topic.

Table 1. Clustering Coefficients of the Entire Network Structure and the Core Network Structure.

	Entire Network Structure	Core Network Structure
Watts–Strogatz Clustering Coefficient	0.05305657	0.12523657

As can be seen in Figure 3, the top five nodes were No.53, No.100, No.32, No.26, and No.144 (based on degree; in-degree and out-degree). Media and organization nodes, with the latter comprising student groups in university, had greater advantages in the core network structure. We compared the degrees of both in the entire interactive network structure and the core network structure (Table 2). The results showed that those media nodes (No. 53, No. 32, No. 26) tended to receive attention from many other users, so their participation is higher. However, these relations often happened onetime, and there were few nodes that can further interact with them. In contrast, although those organization nodes (student groups) did not receive a lot of attention in the entire interactive network structure, their interactions were deepening and continuous; hence, they stood out in the core network structure.

Table 2. Comparison of the Top Five Nodes Based on Degree.

	In-degree in the entire structure	Out-degree in the entire structure	All in the entire structure	All in the core structure
No. 53	257	2	259	24
No. 100	0	23	23	21
No. 32	261	0	261	20
No. 26	121	2	123	18
No. 144	21	3	24	15

We also found that most nodes in the left part of the core network structure came from Fuzhou University, China. These were student groups and individual student users. The nodes in the right part of the core network structure belonged to media, organizations, government sectors, enterprises, and individuals. We paid special attention to nodes No. 1, No. 24, No. 49, No. 52, and No. 125. These five nodes act as three bridges (three edges) connecting the two parts. When we regarded the left and right parts as a whole respectively, these five nodes enabled the flow of policy information and views across the two parts via these three edges, thereby forming the core network structure.

The nodes that showed importance in the core network structure should also have certain importance in the entire network structure. For this reason, we placed these 10 nodes back into the entire structure to investigate their importance in the policy network structure. Table 3 reveals that the degree centrality of No. 32 and No. 53 were significantly higher than others. This implies that the propagation volumes of media and government sectors nodes are larger. Only No. 1, No. 26, No. 53, and No. 144 exhibited betweenness in the structure. In other words, the betweenness centrality of student groups was higher than that of the government sector, media, and enterprises. With regard to closeness centrality, these 10 nodes showed their closeness to other nodes in the structure. Therefore, they were important nodes in the policy network structure. From these three indicators, we can say that government sectors and media nodes played a relatively important role in the policy network structure, and student groups nodes showed a certain role in promoting policy communication. However, individual influence was not obvious.

Table 3. Comparison of Nodes in the Entire Structure.

	Attribute	Degree Centrality	Between Centrality	Closeness Centrality
No. 1	Enterprise	0.016454	0.000276	0.120148
No. 24	Student Group	0.008731	0	0.106392
No. 26	Media	0.041303	**0.001610**	0.107283
No. 32	Media	**0.087643**	0	0.111987
No. 49	Government Sector	0.007052	0	0.126875
No. 52	Media	0.010074	0	0.103030
No. 53	Government Sector	**0.086971**	**0.001311**	0.120148
No. 100	Student Group	0.007723	0	0.126675
No. 125	Student Group	0.014775	0	0.128294
No. 144	Student Group	0.008059	**0.003497**	0.099024

Discussion

The entire communication network of the Mass Entrepreneurship and Innovation policy on social media was constructed by the user nodes and their relationships. These nodes included media, government sectors, organizations, enterprises, and individual users. They interacted on social media based on their concerns about the policy topic and built relationships through comments, forwarding, and likes. With the continuous deepening of interactions, some connections had become closer, and the exchange of policy information had also deepened. Consequently, a core network appeared and promoted the communication of the policy on social media. We studied the entire communication network structure and the core network structure. The findings revealed the characteristics of the policy communication network.

First, the study results showed the composition of the entire network structure, which comprised a core network structure, some numerous scattered subgroups, and independent nodes. This may be because of the different ways and degrees of users' participation in their interaction about policy topics. For example, the nodes of media and government sectors are more outstanding in terms of degree centrality (highest DC of media = 0.087643 vs. highest DC of the government sector = 0.086971). Government sectors are the issuing agencies of policies, while media users may pay more attention to official news. However, individual users may tend to get information from people around them (Gibbon & Pokhrel, 1999). As for the core network structure, nodes converged more closely than those in the entire network structure. Users in the core network structure had built closer relations based on the policy topic, and their interactive behavior greatly promotes the communication of policy information in the interactive network structure. For the numerous scattered subgroups, these core nodes help to expand the dissemination of policy information in the interactive network, but there was a lack of deep interaction among members of such subgroups. Meanwhile, some users may have just browsed the policy information and simply participated in the discussion without paying too much attention to the policy contents; consequently, they become independent nodes. Although they were also involved in the interaction as a whole, their contribution to policy communication was very limited.

Second, the results suggested that different user nodes had different roles in the policy network structure. We found that the media and student group nodes had greater advantages in the core network structure. They both showed their characteristics in terms of betweenness centrality (highest BC of media = 0.001610, highest BC of Student Group = 0.003497). However, their influences were different. Media nodes tended to receive attention from many other users, and these relations often happened onetime. In contrast, although the student group nodes did not receive a lot of attention in the entire interactive network structure, their interactions were deepening and continuous. This may be because the media nodes pay more attention to the coverage or the amount of communication, while in student groups, members pay more attention to the degree of connection between each other. Connections will be closer among members who share the same background or attributes. Moreover, they will be more willing to conduct multiple interactions to strengthen their connection (Ellison, Steinfield, & Lampe, 2007; Helliwell & Putnam, 2004).

To our surprise, most nodes in the core network structure were from Fuzhou University. Out of 210 nodes in the core network, we observed higher activity among 98 nodes, consisting of student groups and individuals within these groups. We tried to investigate the underlying reasons by searching the portal and campus forum of Fuzhou University. It was found that in 2015, Fuzhou University organized many training programs, lectures, and practical activities related to entrepreneurship among college students. Another noteworthy aspect is that the management departments of Fuzhou University also registered accounts on the Sina Weibo platform. Thus, they employed Sina Weibo as a tool to release entrepreneurship policies and information related to college students, similar to what the governments have done in recent years (Mickoleit, 2014). These were major reason why students were more likely to participate in the policy discussions, so much so that it had caused a strong reaction.

In addition, we carried out statistical analysis of the key nodes in the core network structure. Based on degree centrality, betweenness centrality, and closeness centrality, we found that the government and media nodes played a relatively important role in the policy network structure, while student group nodes played a role in promoting policy communication. These highly central nodes were at a structural advantage to exchange policy information (Borgatti & Everett, 2000) and may serve as points of contact to lesser-connected nodes to support efforts at understanding and implementing the policy (Honig, 2008; Wasserman & Faust, 1994). In effect, while a policy may prescribe particular implementation processes, it is ultimately the social ties between individuals that may determine the shape, diffusion, and success of any policy (Spillane, Reiser, & Reimer, 2002). However, in this study, individual influence was not evident. We believe that this is because of the restrictive nature of social media platforms where, for example, compared with media, government sectors, and other types of users, personal posts have relatively few opportunities to receive attention because of their small number of fans/followers.

The distinguishing factor of our study from previous policy research using SNA lies in its incorporation of the public, namely policy audiences, as an integral and crucial part of the network structure. This distinction is driven by several reasons. First, the policy implementation phase inherently involves public participation (Saito, 2021). Our study delves into the network structure of policy communication after policy implementation, rather than focusing on the actor network during policy formulation. This results in a larger number of audience nodes within the policy communication network. Second, relationships are formed freely on social media (Men & Tsai, 2012). We situated the policy communication network within social media platforms, where communication is not confined by social class or identity, enabling direct interactions and thus leading to a more intricate network of relationships. Third, the policy communication network structure is more prone to change. In contrast to the relatively stable actor network structure during policy formulation (Kooij, 2017), social media–based policy communication networks are susceptible to structural alterations influenced by unforeseen events.

Conclusion

We used SNA to analyze the communication network structure of the Mass Entrepreneurship and Innovation policy on social media. SNA helps in perceiving and investigating, through visual means and quantitative measures, the relationships that were constructed as a result of interactions related to the policy. We can consider this network structure to be a result of policy communication on social media. At the same time, it can also be regarded as a target of policy communication, because policy makers want to establish such a network structure on social media to disseminate the policy. The results highlighted that a relatively concentrated interactive group, some numerous scattered subgroups, and independent nodes constitute the entire network structure. In the core network structure, different user nodes played different roles in the policy network structure. Nodes associated with government sectors and the media played a relatively important role in expanding the scope of communication and are at a more advantageous position with regard to deepening interaction.

These findings have broad practical implications. First, attention should be directed toward the nodes within the social media policy communication network to gain insights into the engagement of policy audiences in policy communication. Policy makers should closely track and observe key nodes, such as opinion leaders, ensuring that their content aligns with positive policy perspectives, thus mitigating the potential negative impact on policy communication.

Second, it is essential to focus on the relationships between nodes within the social media policy communication network, identifying active clusters or groups. Since the fission of subgroups in the Internet communication network further challenges the local government’s crisis management, policy making, and integration capability (Wang & Wei, 2019); moreover, continuous attention needs to be paid to these subgroups. Key features can be clearly revealed and nodes that have a greater impact on the network structure can be identified along with their relationships.

Third, continuous monitoring of the structure of the social media policy communication network is crucial. In the event of sudden changes in the network, we can quickly identify key nodes and relationships that may lead to unforeseen circumstances. This proactive approach allows for timely intervention, especially when negative sentiments arise, to manage potential crises and prevent adverse effects on policy communication.

Moreover, the findings in our study provide important reference for the effective communication of policies and certain measures should be adopted to avoid or minimize negative impacts in the policy communication on social media. For example, on account of the relatively important role government sectors and media nodes played in the policy network structure, it is possible to expand the boundaries of the policy communication network through continuous and large-scale reports. It is necessary to adopt different communication strategies for policy audiences with different attributes. As innovation and entrepreneurship is an important topic for college students, positive guidance across student group nodes may generate interest among policy topic participants about policy themes (Petridou, Becker, & Sparf, 2021).

Furthermore, it is important to note that although our case study focuses on China’s innovation and entrepreneurship policy, this study can also offer valuable insights to other developing countries in innovation policy research, since innovation policies have become a crucial strategy for promoting development in various countries. Additionally, with the widespread use of social networks, other countries’ public policies that are closely related to the public can also be analyzed to understand the dissemination characteristics of policies on social media platforms. By applying SNA to study different policy contexts, we can gain valuable insights into the dynamics of policy communication networks, identify key actors and relationships, and understand how policy information flows on social media.

However, there are several limitations in this study. First, the analysis did not capture the entire network dynamics or its evolution, as insights were only provided for the first year after the policy release. Additionally, because of the possibility of users changing their privacy settings on Sina Weibo, data before six years could not be obtained, limiting the scope of the study. To overcome these limitations, future studies could focus on conducting a long-term effect evaluation with real-time data acquisition, providing a more comprehensive understanding of the network dynamics over time. Furthermore, adding sentiment tags to the nodes in the core network and examining connections with more negative emotions could be valuable for a future study. Monitoring the emotions of participants on policy topics can help identify potential issues in the policy communication process. Another noteworthy limitation is that the incorporation of new concepts in policy networks, such as collaborative policy networks, offers a promising framework for future research. By exploring these emerging concepts, researchers can gain deeper insights into the complexities of policy communication and its impact on the public and stakeholders.

References

Amjad, K., Saeed, M., Ali, F., & Awais, M. (2020). Social media use and political polarization: Political engagement as a mediator. *The Journal of Social Sciences Research, 6*(8), 804–810. doi:10.32861/jssr.68.804.810

Borgatti, S. P., & Everett, M. G. (2000). Models of core/periphery structures. *Social Networks, 21*(4), 375–395. doi:10.1016/S0378-8733(99)00019-2

Bou-Karroum, L., El-Jardali, F., Hemadi, N., Faraj, Y., Ojha, U., Shahrour, M., . . . Akl, E. A. (2017). Using media to impact health policy-making: An integrative systematic review. *Implementation Science: IS, 12*(1), 52–66. doi:10.1186/s13012-017-0581-0

Cahyani, I. P. (2019). Understanding the new media literacy in spreading hoaxes and hate speech. *Book Chapters of The 1st Jakarta International Conference on Social Sciences and Humanities (JICoSSH), 3*, 247–269. doi:10.33822/jicossh.v3i0.18

Charalambous, A. (2019). Social media and health policy. *Asia-Pacific Journal of Oncology Nursing, 6*(1), 24–27. doi:10.4103/apjon.apjon_60_18

Clarke, A., & Margetts, H. (2014). Governments and citizens getting to know each other? Open, closed, and big data in public management reform. *Policy & Internet, 6*(4), 393–417. doi:10.1002/1944-2866.POI377

Davies, R. (2009). *The use of social network analysis tools in the evaluation of social change communications. An Expanded M&E Framework for Social Change Communication*. Retrieved from https://richardjdavies.files.wordpress.com/2009/08/the-use-of-social-network-analysis-tools-in-the-evaluation-of-social-change-communications-c.pdf

Drew, R., Aggleton, P., Chalmers, H., & Wood, K. (2011). Using social network analysis to evaluate a complex policy network. *Evaluation, 17*(4), 383–394. doi:10.1177/1356389011421699

Ellison, N. B., Steinfield, C., & Lampe, C. (2007). The benefits of Facebook "friends:" Social capital and college students' use of online social network sites. *Journal of Computer-Mediated Communication, 12*(4), 1143–1168. doi:10.1111/j.1083-6101.2007.00367.x

Farine, D. R., & Whitehead, H. (2015). Constructing, conducting and interpreting animal social network analysis. *Journal of Animal Ecology, 84*(5), 1144–1163. doi:10.1111/1365-2656.12418

Gibbon, M., & Pokhrel, D. (1999). Social network analysis, social capital and their policy implications. *PLA Notes, 36*, 29–33. IIED London.

Helliwell, J. F., & Putnam, R. D. (2004). The social context of well-being. *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences, 359*(1449), 1435–1446. doi:10.1098/rstb.2004.1522

Himelboim, I., Smith, M., & Shneiderman, B. (2013). Tweeting apart: Applying network analysis to detect selective exposure clusters in Twitter. *Communication Methods & Measures, 7*(3–4), 195–223. doi:10.1080/19312458.2013.813922

Honig, M. I. (2008). District central offices as learning organizations: How sociocultural and organizational learning theories elaborate district central office administrators' participation in teaching and learning improvement efforts. *American Journal of Education, 114*(4), 627–664. doi:10.1086/589317

Huang, L. C., Zhao, Y. P., Liu, C. W., Wu, F. F., & Li, X. Y. (2018). Microblog-oriented public "mass innovation and entrepreneurship" hotspot identification and sentiment analysis and policy suggestions. In *Proceedings of the 2018 International Conference on Management Science and Engineering (ICMSE)* (pp. 138–148). Berkeley, CA: IEEE Publications. doi:10.1109/icmse.2018.8744981

Jungherr, A. (2016). Twitter use in election campaigns: A systematic literature review twitter use in election campaigns: A systematic literature review researching uses of twitter in election campaigns. *Journal of Information Technology & Politics, 13*(1), 72–91. doi:10.1080/19331681.2015.1132401

Kalantari, E., Montazer, G., & Ghazinoory, S. (2021). Mapping of a science and technology Policy Network based on social network analysis. *Journal of Entrepreneurship, Management and Innovation, 17*(3), 37–66. doi:10.7341/20211734

Keqiang, L. (2014, September, 12). Creating new dynamism through reform and innovation. *China Daily*. Retrieved from http://www.chinadaily.com.cn/opinion/2014-09/12/content_18585913.htm

Knoke, D. (2018), *Changing organizations: Business networks in the new political economy*. New York, NY: Taylor & Francis. doi:10.4324/9780429501753

Kooij, H-J. (2017). Mediating policy competition through campus development in Dutch Limburg. *Tijdschrift Voor Economische en Sociale Geografie, 108*(6), 869–878. doi:10.1111/tesg.12238

Kozyreva, A., Lewandowsky, S., & Hertwig, R. (2020). Citizens versus the Internet: Confronting digital challenges with cognitive tools. *Psychological Science in the Public Interest, 21*(3), 103–156. doi:10.1177/1529100620946707

Kumar, S., & Panda, B. S. (2020). Identifying influential nodes in social networks: Neighborhood coreness based voting approach. *Physica A: Statistical Mechanics and its Applications, 553*(9), 124215–124228. doi:10.1016/j.physa.2020.124215

Lilleker, D., Jackson, D., & Thorsen, E. (2016). *US election analysis 2016: Media, voters and the campaign*. Poole, UK: The Centre for the Study of Journalism, Culture and Community, Bournemouth University. Retrieved from https://www.electionanalysis2016.us/

Malathi, A., & Radha, D. (2016). Analysis and visualization of social media networks. In *Proceedings of the 2016 International Conference on Computation System and Information Technology for Sustainable Solutions (CSITSS)* (pp. 58–63). Berkeley, CA: IEEE Publications. doi:10.1109/CSITSS.2016.7779440

Mathias, K. H., Hans-Bernd, B., & Friedrich, S. J. (1991). Opinion formation in mediated conflicts and crises: A theory of cognitive-affective media effects. *International Journal of Public Opinion Research, 2*, 132–156. doi:10.1093/ijpor/3.2.132

McIntyre, L., Jessiman-Perreault, G., Mah, C. L., & Godley, J. (2018). A social network analysis of Canadian food insecurity policy actors. *Canadian Journal of Dietetic Practice and Research, 79*(2), 60–66. doi:10.3148/cjdpr-2017-034

Men, L. R., & Tsai, W. H. S. (2012). How companies cultivate relationships with publics on social network sites: Evidence from China and the United States. *Public Relations Review, 38*(5), 723–730. doi:10.1016/j.pubrev.2011.10.006

Mickoleit, A. (2014). *Social media use by governments: A policy primer to discuss trends, identify policy opportunities and guide decision makers*. Paris, France: OECD Publishing. Retrieved from http://www.oecd-ilibrary.org/docserver/5jxrcmghmk0s-en.pdf?expires=1665973627&id=id&accname=guest&checksum=2351936E4186B35B9D7B62B71A6399F5

Petridou, E., Becker, P., & Sparf, J. (2021). Policy entrepreneurs in public administration: A social network analysis. *Politics and Policy, 49*(2), 414–445. doi:10.1111/polp.12400

Rethemeyer, R. K., & Hatmaker, D. M. (2007). Network management reconsidered: An inquiry into management of network structures in public sector service provision. *Journal of Public Administration Research and Theory, 18*(4), 617–646. doi:10.1093/jopart/mum027

Saito, H. (2021). The developmental state and public participation: The case of energy policy-making in post–Fukushima Japan. *Science, Technology, & Human Values, 46*(1), 139–165. doi:10.1177/0162243920905000

Spillane, J. P., Reiser, B. J., & Reimer, T. (2002). Policy implementation and cognition: Reframing and refocusing implementation research. *Review of Educational Research, 72*(3), 387–431. doi:10.3102/00346543072003387

Stankevice, I. (2014). Innovation strategies: The patterns across countries: Industries and firm competitiveness. *European Scientific Journal, 1*, 187–199. Retrieved from https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.966.3889&rep=rep1&type=pdf

State Council of The People's Republic of China. (2018). *Opinions on promoting the high-quality development of innovation and entrepreneurship and creating an upgraded version of "mass entrepreneurship and innovation."* Retrieved from https://www.gov.cn/zhengce/content/2018-09/26/content_5325472.htm

Stolle, D., Hooghe, M., & Micheletti, M. (2005). Politics in the supermarket: Political consumerism as a form of political participation. *International Political Science Review, 26*(3), 245–269. doi:10.1177/0192512105053784

Vanderelst, D. (2015). Social network analysis as a tool for research policy. *PLOS Neglected Tropical Diseases, 10*(1), e0004410–e0004413. doi:10.1371/journal.pntd.0004410

Wang, J. D., Tong, N. N., & Yi, C. Q. (2019). *The transformation of public policy assessment in the age of big data*. Beijing, China: Social Science Literature Press.

Wang, L., & Wei, Y. (2019). Hyper-network analysis of policy communication on social media. In *Proceedings of the 20th Annual International Conference on Digital Government Research* (pp. 517–519). Amsterdam, The Netherlands: IOS Press. doi:10.1145/3325112.3328219

Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications*. Cambridge, UK: Cambridge University Press.

Zhang, A. X., & Counts, S. (2015). Modeling ideology and predicting policy change with social media: Case of same-sex marriage. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems* (pp. 2603–2612). Seattle, WA: ACM. doi:10.1145/2702123.2702193

Zhang, Z. F., Li, X. L., & Gan, C. Q. (2021). Identifying influential nodes in social networks via community structure and influence distribution difference. *Digital Communications and Networks, 7*(1), 131–139. doi:10.1016/j.dcan.2020.04.011