Knowledge Development in Communities During Crises: a Discourse Comparison Tool

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September 7, 2023

KNOWLEDGE DEVELOPMENT IN COMMUNITIES DURING CRISES: A DISCOURSE COMPARISON TOOL

Research full-length paper

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Abstract

How is the development of knowledge in communities affected by disaster events? We present a state-of-the-art tool that provides the ability to compare discourses in communities, by converting text messages to communication graphs and enabling graph comparison visualization.

The tool's validation includes conversion of chats from 81 WhatsApp groups to graphs and comparison between them, after divided to time-periods around a global crisis.

Results indicate that (1) density is reduced during crises, meaning that communication decreases, (2) There is no change in network influencers between periods of times during the crisis, (3) there is a direct effect of the nature of a time-period on the nature of discourse in the community and (4) The suggested tool is suitable for communication graph comparison.

The contribution of the current research is a novel approach to measure and compare knowledge development in communities using a graph comparison tool. This study represents a progress in understanding the differences in communication during different times of crises in communities.

Implications of the research relate to mechanism for communication comparison including visualization and analysis. The ability to identify communication patterns in communities assists in understanding the development of collective knowledge.

Keywords: Information systems, knowledge development, communication graphs, graphs comparison

1 Introduction

The ability of users on Twitter to retweet information has made Twitter one of the most prominent social media platforms for disseminating emergency information during disasters. According to the literature on disaster communication - risk communication and crisis communication occur at different stages during a disaster. These two types of communication represent a real-time exchange of messages regarding survival, health, and economic and social well-being. Crisis communication occurs in times of crisis to address the situation, while risk communication aims to prevent a crisis. During disasters, the impact of Twitter's media capabilities on rapid tweet propagation may differ, based on the communication processes.

Communities routinely work together to survive and recover from the impact of catastrophic events. The current study distinguishes between communities that are created as part of the goal to deal with a global disaster, and everyday communities that were established before the disaster, continue to exist during it and survive after the disaster ends. Question arises regarding the influence of global events and crises on communication in these everyday communities. Hence, the current research's main goal is to examine differences in knowledge development during different periods of global events.

Social network analysis is used to understand communication and interactions within a community. In order to examine the differences in knowledge development among everyday communities, a method is required to measure communication. In addition, the ability to compare the discourses is required. The measurement method that this research makes use of is converting text messages into a communication graph and developing a scientific tool for comparing graphs using Social Network Analysis (SNA) methods.

Using the scientific tool for graphs comparison, we compared 81 chat conversations from different periods of time around global events.

Results indicate that (1) density is reduced during crises in everyday communities. Meaning that communication decreases, (2) There is no change in network influencers between periods of times during the crisis, (3) there is a relationship between the time-period and the structure of the network. Meaning, there is a direct effect of the nature of a period on the nature of the discourse, which is expressed in the communication graph between the entities and (4) The test case we tested verifies the effectiveness of the proposed tool for comparing communication graphs.

Implications of the current research relate to mechanism for communication comparison including visualization and analysis. In addition, the ability to identify communication patterns in everyday communities, allows us to deal with the development of collective knowledge in a rational, orderly and controlled manner.

2 Theoretical Background

This section begins with a brief description of communication during crises and global events, including explanations regarding how we develop indicators for measuring knowledge production based on information-sharing interactions between community members. Finally, this section describes research done recently in the fields of social networks analysis, measurement and comparison of social networks.

2.1 Knowledge Development During Global Events

We referred to the claim that sharing information is one of the elements in the production of knowledge in a community. It has been claimed that in crises situation, almost everything is an exception to the norm (Turoff et al., 2009). Specific communication systems are involved in order to manage the disaster (Murayama, 2014), emergency response information systems provide communities collaborative knowledge systems to exchange information (Turoff et al., 2009). The use of social media for to communicate critical information during crisis situations, in particular Twitter, has become a standard in recent years (Olteanu et al., 2015). On the one hand, crowd-sourced information has rapidly become an essential source of data in disaster response (McClendon & Robinson, 2012) and therefor it may be expected that knowledge development during crises will increase. On the other hand, how will knowledge be developed in times of uncertainty and who will contribute to the knowledge development?

During crises and global events misalignment occurs between what companies mean to communicate and what employees perceive. Companies can plan excellent communication and describe the crisis as an opportunity, while employees experience negative communication (Mazzei & Ravazzani, 2011). Major crises affect the institutions that people trust. During crises people trust scientists more than they trust government officials (Haynes et al., 2008). Trust is important because every society maintains a certain level of trust among its members, which results in some level of cooperative behavior between them (Fukuyama, 2002).

In light of the contradiction between the need to develop critical knowledge during a crisis and organizational and individual cognitive changes during periods of uncertainty, we seek to understand the processes that affect knowledge production during crises and uncertainty in social communities.

One way to understand and measure knowledge production in a social network, is by referring to text interactions between members. Persistent information sharing in virtual platforms leads to the appearance of interactivity. Given that person A communicates with person B using a computer software, interactivity is defined as the degree of B's reaction (Rafaeli & Sudweeks, 1998). Interactivity is a psychological factor which varies across communication technologies, contexts, and perceptions (Kiousis, 2002). Organizations should strive to enhance interactivity and information sharing, while considering attitudes of people (Pai & Yeh, 2014). This study refers to organizations engaged in the production of knowledge during crises, where information sharing between members of the community is carried out through interactions among its members.

Referring to the conflict between the rush to consume information in times of crisis and the relaxation of the need to create information and thus develop knowledge in everyday social communities, this study leads to hypothesize the following hypothesis:

H1: During crises, knowledge development in everyday communities decreases

Regarding leaders and influencers in the social community, there are once more two perspectives. From the perspective of communication professionals such as governments, presidents, prime ministers and other authorities, they strive to provide critical and timely information in order to manage the crises. The public trust decline when fake or alternative stories are provided (Jong, 2020). Influencers in social networks have demonstrated capacity to create and disseminate information that reaches and influences a large number of people, however, this specific capability is not necessary related to a professional official status (Ingenhoff et al., 2021). Hence, from the perspective of social communities, in stable communities which were created before a crisis, there is not expected to be a change in the identity of influencers.

Hence, the current research second hypothesis is:

H2: During crises there is no change in everyday communities' influencers

The following section elaborates on comparison between social networks using SNA methods.

2.2 Networks Comparison Using Social Network Analysis Methods

Social networks represent social relationships between pairs or among groups of social units such as friendships among students and pupils in classrooms (DeLay et al., 2016; Naim et al., 2010; Rienties et al., 2013) or the movement of a football among players on the field (Clemente et al., 2015; Mclean et al., 2019). Modeling such networks as graphs, representing participants by nodes and connections by arcs allows analysis and generation of meaningful insights relating to behavior and interaction among the members of a network. Network analysis makes it possible to gain significant insights in the sphere of social skills as well. For example, trust and problem solving can be measured using SNA methods, using the results to increase success (McGhee Hassrick et al., 2021). Another example relates to the analysis of social influences. Using network analysis, it is possible to measure a user's direct and indirect social impact on other users within a mobile phone social network (Peng et al., 2017).

Online conversation platforms enable information sharing, thereby developing knowledge. By definition, every participant in an online communication group such as WhatsApp, receives information. This information is then often conveyed onward by sharing or forwarding it. When a team shares information, there is a positive impact on performance (Rusho & Raban, 2019, 2021). Communication can be analyzed using techniques of social network analysis. For example, understanding email communication between corporate managers (Nayak & Agarwal, 2011; Rowe et al., 2007), or understanding interactions among users during disasters via social media (Kim & Hastak, 2018). By analyzing social interactions during a crisis between individuals and entities, crisis management entities can be assisted to develop social media activation strategies for a disaster reduction program.

One of the key promising possibilities of the social network analysis paradigm is that in many cases, the structure of the network is defined by the behavior of the members. For example, a network structure of a knowledge generating discussion is different from the network structure of an administrative Q&A discussion (Aviv & Ravid, 2005).

In terms of measurements, Wilkin, Biggs and Tatem (Wilkin et al., 2019) described how Network-based measures (NBM), which are a mathematical evaluation of a network structure, can be linked with other measures of norms, trust and reciprocity to provide local and conceptual quantification regarding social capital (2019).

Network structure, such as density, reciprocity and transitivity reflect the nature of the community they represent. The density of a network is defined by the ratio of the number of extant ties in a network to the number of all possible ties, i.e., the proportion of potential connections in a network that are actual connections.

The density of a network may provide insights into phenomena such as the speed at which information diffuses among the nodes (Izquierdo & Hanneman, 2006) and the level of the nodes' interactivity. In an interaction network, density can be used to measure the level of a node's embeddedness in the discussions. A dense interaction network is one where everyone responds to everyone else within the network.

Transitivity refers to the tendency of the nodes to cluster together and reciprocity refers to responding to a one action with another action.

Referring to the fact that the discourse in the everyday community takes place during a crisis and the discourse indicators are affected by the non-digital reality of a period of uncertainty, following is the third hypothesis:

H3: There is a positive relationship between network structure that represents knowledge development in everyday communities, and the period in which it takes place.

Prell and Skvoretz (2008) address how the presence or absence of trust and reciprocity is reflected in a network's structure. They state that "network closure" refers to the case where network actors are tied to one another through mutual reciprocation, in other words, through strong ties. Trust is transitive, and as trust may decrease during crises, it is therefore requested to examine the difference in network structure: transitivity, reciprocity and density between different periods, between which a crisis occurred.

Thus, it is necessary to compare graphs of knowledge development in different periods. The available literature mainly discusses activity patterns in the context of individual case studies, but there is a lack of comparative research on communicative events and their dynamics and patterns on a larger scale (Bruns & Stieglitz, 2012). Comparisons can be performed using algorithms; the software system can then output visualizations by displaying the resulting graphs. Existing software packages include Gephi, which assists in the formation of hypotheses and discovering patterns through data analysis, and Cytoscape, which is a general platform for complex network analysis and visualization.

Network comparison aims to account for properties that are generated by the simultaneous interaction of all units in the network rather than the individual properties of every member; for example, by showing and highlighting "significant" changes in network evolution. A particular characteristic of interest could be the speed of information flow, which can be used to quantify how "close" two networks are. The obvious difficulty in comparing networks is that there is no clear way to compare networks as complete, integral entities. Researches use different methods to compare between networks, such as machine learning for classification of real memes (Ratkiewicz et al., 2011), mathematical calculations in order to compare users' behavior and activities on Twitter (Hodas et al., 2013).

3 Method

This research explores the effect of global crises on knowledge production in everyday communities using the analysis and comparison of WhatsApp conversations. Each conversation was cleaned from content, leaving only timestamp and members identifiers. Next, each cleaned conversation was divided to periods of time and converted to a sequential trio of the message sender, the message receiver and timestamp. Each conversation then was represented as a DiGraph using Python, network measures were calculated, networks were compared and CSVs were exported for statistical tests.

Subjects: 15 communities, divided into 6 periods, which form 81 networks, as described in Table 1.

	Time Period	Frequency	Description
1	Before March 2020	15	Before the Covid
2	March 2020 - August 2020	14	The outbreak of the Covid epidemic. Extensive closures
3	September 2020 - February 2021	13	The peak of the Covid. Before vaccinations
4	March 2021 - August 2021	15	After vaccinations
5	September 2021 - February 2022	12	Relaxation
6	March 2022 – May 2022	12	Fifth and last wave. Feel that the worst is behind
Total		81	

Table 1. Conversations' frequencies divided to time periods

Variables: The independent variables were (1) in hypotheses 1,2: time periods and (2) in hypothesis 3: network metrics (density, reciprocity, transitivity, self-loops and centralizations).

3.1 Procedure

In order to examine information sharing and knowledge development in diverse communities, this study aims to compare graphs that represent the discourse in these communities. To this end, a tool is required for enabling both converting the conversation into a graph, and the ability to compare graphs. The following sections detail the graph comparison tools.

3.1.1 Graph Comparison Tool

The graph comparison tool focuses on both goals: (1) converting a discourse to a graph, and (2) making comparisons within a particular graph in different time frames.

In order to build the communication graph, the tool loads WhatsApp text messages and builds a directional graph, where each participant is a node, and the weight of each arc is the sum of responses sent between these nodes.

In order to compare between networks, Figure 2 illustrates the process of dividing a conversation from a WhatsApp group to periods and to sequential text messages. A txt file is exported from WhatsApp consists of rows of interactions. Using the suggested tool, this file is divided into time-periods. In the large squares the structure of the interactions is displays.

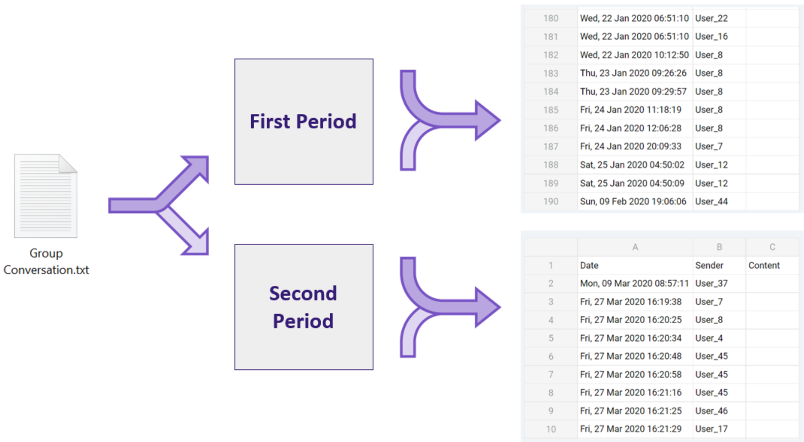

Figure 2. Dividing a conversation to periods and texts

The tool enables a large display of each graph, including statistics, as shown in Figure 3. The graph is shown on the left. In the current example, the red circles represent the shortest path between two entities, according to selected attributes on the right. The user can select to highlight individual metrics: Degree centrality, closeness centrality, betweenness centrality. In addition, the user can choose to highlight local metrics: reciprocity, diameter, radius, transitivity. Clicking the "global measures" displays: Average degree, degree distribution and path length.

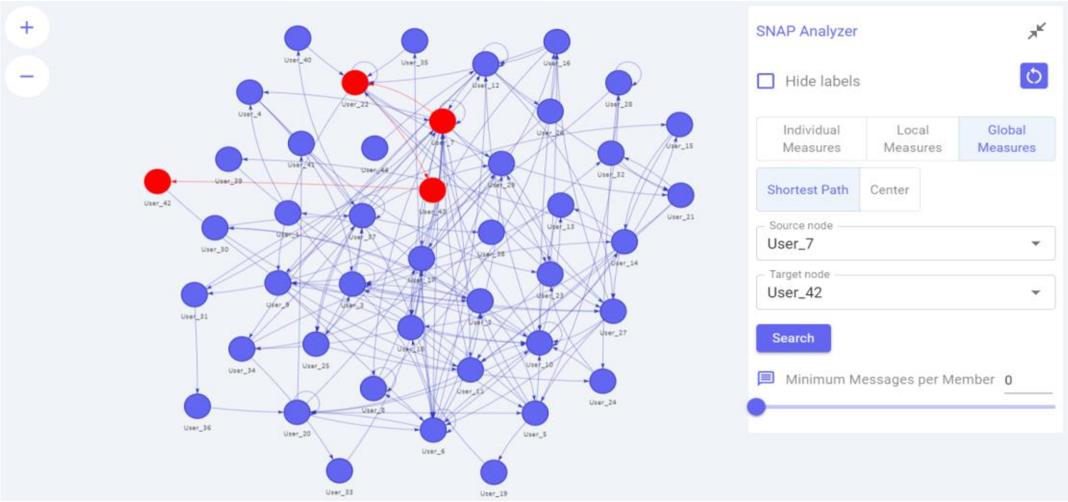

Figure 3. Network screen with all measurements in the graph comparison tool

Figure 4 displays a comparison between four periods of time, of the same group conversation.

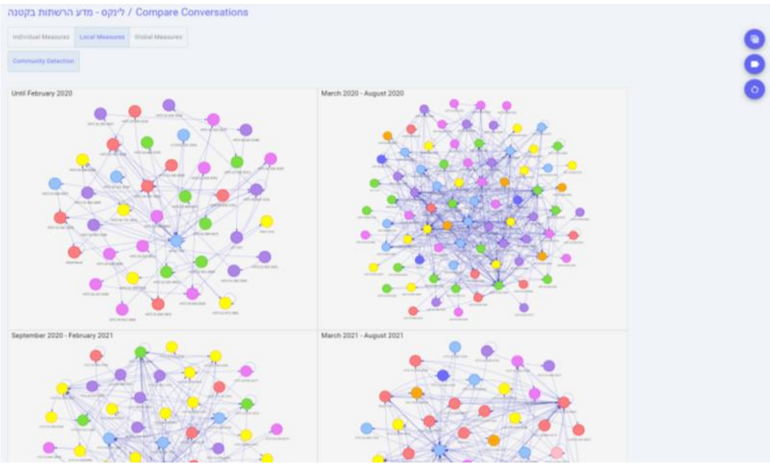

Figure 4. The graph comparison screen

Due to different sizes of groups, all centrality measurements had to be adjusted, to be in relation to the group size. A calculation of network centralization is required in order to compare centrality measures at the node level to the graph level. For example, given a graph with 40 nodes and a graph with 4 nodes, the maximum degree centrality that can be in the small graph will be smaller than the maximum in the large graph, because the number of nodes in this graph is smaller. In order to solve this problem, we calculated network centralization by the following formula, according to (Sociology & 2002, 1978):

$$\frac{\sum_{i=1}^{N}(C(v_*) - C(v_i))}{(N-1)(N-2)}$$

In the numerator: performing calculation of the centrality measure (degree, betweenness, closeness) of each node in the graph, finding the maximum and subtracting the value of the node from the maximum value. After that, perform an addition operation of all these values.

In the denominator: $(N-1)(N-2)$ where N is the number of nodes in the graph.

4 Results

Descriptive statistics of the dependent variables are displayed in Table 2, divided to six time-periods: first period (before March 2020), second period (March 2020 - August 2020), third period (September 2020 - February 2021), fourth (March 2021-August 202, fifth period (September 2021 - February 2022) and the sixth period (March 2022 – May 2022):

Time Period		Nodes	Edges	Diameter	Radius	Density	Transitivity	Reciprocity	Degree Centralization	Closeness Centralization	Betweenness Centralization
1	Mean	27.87	175.47	3.73	2.27	0.56	0.50	0.56	0.10	0.03	0.08
	Std. Deviation	28.24	217.95	2.22	1.44	0.47	0.34	0.20	0.25	0.08	0.26
	N=15										
2	Mean	26.64	180.50	3.43	1.86	0.61	0.52	0.57	0.11	0.04	0.09
	Std. Deviation	27.48	197.61	1.79	1.03	0.47	0.38	0.25	0.26	0.09	0.26
	N=14										
3	Mean	24.15	177.77	3.92	2.15	0.59	0.58	0.60	0.05	0.01	0.02
	Std. Deviation	23.61	225.66	2.87	1.28	0.45	0.34	0.21	0.08	0.02	0.05
	N=13										
4	Mean	27.67	160.73	5.73	3.13	0.45	0.43	0.48	0.03	0.01	0.01
	Std. Deviation	26.26	213.37	5.19	2.77	0.48	0.39	0.25	0.03	0.01	0.02
	N=15										
5	Mean	48.83	385.17	5.08	2.83	0.19	0.33	0.45	0.05	0.02	0.02
	Std. Deviation	29.89	415.44	1.44	0.72	0.18	0.18	0.13	0.06	0.02	0.02
	N=12										
6	Mean	43.50	246.42	5.42	2.92	0.18	0.27	0.41	0.05	0.01	0.02
	Std. Deviation	30.27	270.49	2.50	1.24	0.21	0.14	0.11	0.05	0.02	0.02
	N=12										

Table 2. Descriptive statistics

H1 results: A one-way between subjects ANOVA was conducted to compare the effect of time periods on communication. There was a statistically significant effect of time period on density $F_{(6,75)}$=2.975, p=.017.

Post hoc comparisons using the LSD test are reported in Table 3. Results indicate that the density in the first period (before March 2020), second period (March 2020 - August 2020) and third period

(September 2020 - February 2021) are significantly higher than the density in the fifth period (September 2021 - February 2022) and the sixth period (March 2022 – May 2022):

Time Period	vs time period	*p*
1	2	0.717
	3	0.857
	4	0.482
	5	0.021
	6	0.020
2	1	0.717
	3	0.863
	4	0.294
	5	0.010
	6	0.009
3	1	0.857
	2	0.863
	4	0.392
	5	0.017
	6	0.016
4	1	0.482
	2	0.294
	3	0.392
	5	0.096
	6	0.092
5	1	0.021
	2	0.010
	3	0.017
	4	0.096
	6	0.985
6	1	0.020
	2	0.009
	3	0.016
	4	0.092
	5	0.985

Table 3. One-Way ANOVA Post Hoc density

Density trend from period 1 to period 6 is shown in Figure 6.

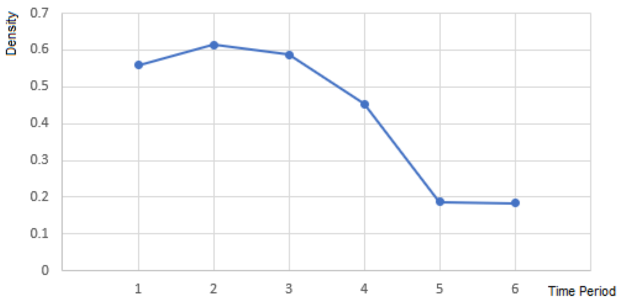

Figure 6. Average density trend during 6 time periods

Hypothesis H1 was accepted. Density is reduced during crises in everyday communities.

H2 results: A one-way between subjects ANOVA was conducted to compare the effect of time periods on network influencers. Network influencers were measured by three graph centralization measurements (mathematical calculations explained above): Degree, Betweenness and Closeness centralities. No statistically significant effect was found between time period to any of the centralities.

Figure 7 displays trends between periods of time and graph centralizations.

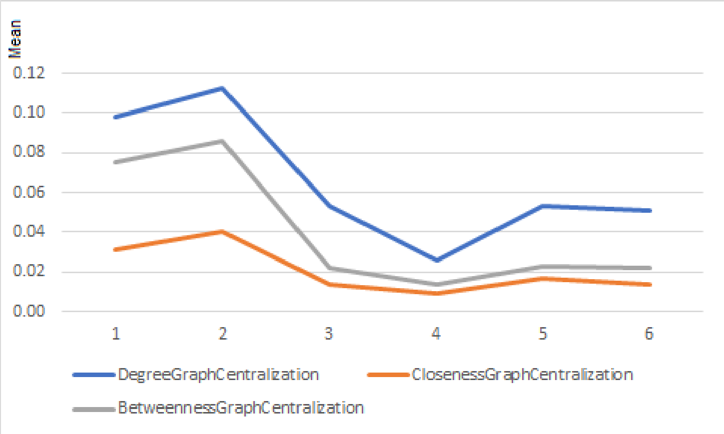

Figure 7. Trends between periods of time and graph centralizations

Hypothesis H2 was accepted. No change in network influencers between periods of times during the crisis.

H3 Results: in order to find relationship between network structure that represents knowledge development in everyday communities, and the period in which it takes place, a K-Means Quick Cluster was conducted on network metrics: diameter, radius, density, self-loops, average clustering, transitivity, reciprocity and the three centralizations: degree, closeness and betweenness. Table 4 displays clusters mean square and statistically significant effect.

Network metrics	Cluster mean square	*p*
diameter	15.46	.000
radius	14.73	.000
density	29.25	.000
self-loops	6.06	.002
average clustering	29.47	.000
transitivity	30.67	.000
reciprocity	25.93	.000
degree centralization	35.67	.000
closeness centralization	34.81	.000
betweenness centralization	38.86	.000

Table 4. K-Means Anova

Figure 8 visualizes the three clusters showing differences among cases in different clusters.

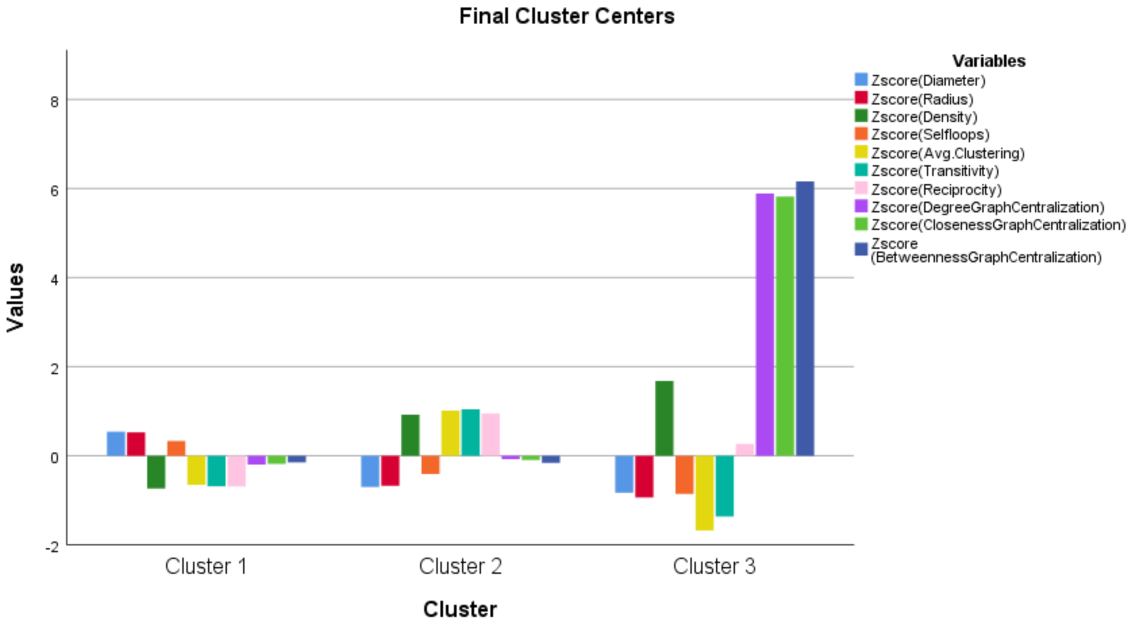

Figure 8. Clustering results

In order to find correlation between clusters, which represent network structures, and time-period, a Pearson test was conducted. There was a statistically significant effect *p*=.001 between network structure and six time periods (descriptive in Table 2) and network structure. In addition, there was a statistically significant effect *p*=.026 between network structure and three time periods (Until February 2020, March 2020 - March 2022, March 2022 - Today) and network structure.

H3 was accepted. Time period affects network structure.

5 Discussion and Conclusion

The current research investigated the influence of crises on knowledge development in everyday communities. Using WhatsApp conversations and statistical methods, we compare and analyse interactions between members in order to understand knowledge production. We apply a novel method, which enables the development of social and collaborative practices. The research tool is a software that provides the ability to compare discourses in communities. It converts text messages exchange between members of the community and displays visualization in a state-of-the-art interface, which enables graph comparison.

In order to validate the suggested tool, we use it to convert 18 WhatsApp conversations from different chat groups, compare communication before, during and at the end of a global crisis and visualize communication metrics in individual, global and local perspectives for effective insights and comparison.

The results we have discovered are surprising. Results show differences in network structure, information flow and therefore, communication patterns between time-periods.

This study is an opening for further research in the field. How does a global epidemic affect the discourse within groups of people who communicate with each other over the years? How do global events affect online interpersonal communication? Are there differences between politics events and health events?

To further answer these questions, we have built the research tool, which allows to compare the discourse online. Using this state-of-the-art graph comparison tool, we are able to continue and compare different communities in different areas, in order to further understand the change in discourse, for better or worse, between children, parents, managers, organizations, government bodies and more.

The insights from this study are significant for understanding the change required in discourse, guidance and aspiration for continued standard and positive communication between bodies and individuals in times of crisis. In addition, in the times after a global crisis, in which one needs to recover from the crisis and continue communication between the people for a positive and healthy future.

In terms of the graph comparison tools, as the field of social network analysis continues to develop, more tools are required to assist in graph analysis, decision making and understanding insights from human social networks. This tool is one of a series of tools that are required in the world of research for comparisons between graphs.

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