HOW TO ANALYZE AND ENHANCE PARTICIPATION IN ELECTRONIC NETWORKS OF PRACTICE

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Abstract: This study proposes an exploratory methodology for analyzing participation in Electronic Networks of Practice, focusing on a network of 500 specialists in breast cancer treatment as a case study. The research addresses a critical gap in understanding how conversational dynamics influence participation in professional forums. Conversation measures and participation measures reported in the literature are identified and categorized, and new ones are suggested. This study by correlation analysis reveals three key participation triggers: initiator features, timing of initiation, and feedback, while also identifying non-associated variables like conversation topic and expression. Clustering categorizes conversations into four types, each exhibiting participation patterns and attributes. Social network analysis further reveals the network's structure and participants' interrelations. These findings provide a comprehensive understanding of participation in Electronic Networks of Practice and show the methodology's broader applicability in analyzing professional networks. The study's insights are vital for practitioners and theorists by offering a perspective on fostering knowledge sharing.

Keywords: Electronic Networks of Practice, Knowledge Sharing, Participation, Conversation, Exploratory Data Analysis.

JEL Classification: C38, D83, D85, M15.

1 Introduction

In an era where technology and digitization are rapidly changing the professional landscape, the role of social networks in professional domains has evolved from occasional use to day-to-day work (Patalas-Maliszewska, 2014; Guan, et al., 2018). With the arrival of emerging technologies, understanding the dynamics of knowledge sharing within these networks has become increasingly critical. This is not only due to the rapid growth and evolving nature of such technologies but also because of their potential to significantly enhance organizational competitiveness and innovation.

990 studies on knowledge sharing, from 1996 to 2006, find the most important topic of the field to be electronic networks, such as communities of practice and social networks (Ahmed, et al., 2019). However, despite the growing interest in and reliance on these networks, the specific ways in which emerging technologies influence and potentially transform knowledge sharing practices remain under-researched. This gap in the literature is particularly clear, given the accelerating pace of technological advancement and its profound impact on professional collaboration and knowledge exchange. A recent study begins to address this gap by identifying key drivers for knowledge sharing in the context of emerging technologies, such as the integration of diverse expertise and the creation of interconnected platforms for effective communication (Tiwari, 2022). However, a comprehensive understanding of how these factors play out in Electronic Networks of Practice (ENoP) and how we can enhance participation in these environments is still lacking. This research aims to fill this gap by exploring the dynamics of knowledge sharing in ENoPs, especially within the rapidly evolving context of emerging technologies.

The emergence of Electronic Networks of Practice (ENoP)—professional social networks that support experts in sharing knowledge with each other—represents a significant shift in how professionals collaborate to solve problems through computer-mediated communication. Wasko and Faraj (2005) define *Electronic Networks of Practice* as networks of professionals who voluntarily participate in knowledge sharing, problem-solving, learning through posting and responding to questions, exchanging personal experiences, and debating relevant issues through computer-mediated communication. In contrast with many online communities and forums, an ENoP is a self-organizing, open activity system focused on a shared practice. (Wasko and Faraj, 2005).

There are a lot of works on ENoPs in academic literature, ranging from studies that focus on why people participate (Pang, et al., 2020) to more traditional social network studies that focus on the network structure (Wang, 2013) and network properties (Wasko, Faraj and Teigland, 2004). In addition, certain works focus on incentives for continued knowledge sharing, such as reciprocity, helping others (Cheung, Lee and Lee, 2013), perceived usefulness (Hashim, Ahmad and Shahranee, 2015), and achievement (Liu and Chen, 2018).

This paper aims to address the critical questions at the heart of knowledge sharing in ENoPs: How can we enhance the participation of the involved specialists in knowledge sharing, and what strategies can sustain participation at a high level? To answer these questions, we conducted an in-depth study of specialist behaviors in professional networks, identifying and analyzing repetitive patterns in the data. These patterns led us to investigate the triggers that initiate conversations and the dynamics that sustain them. We have developed and applied a methodology to measure and analyze actual participation in conversations, focusing on identifying the triggers of higher participation. This methodology involves extracting conversations from the network and employing specific measures to assess participation levels.

The application of this methodology to a network of health specialists has yielded new insights, revealing certain key factors that encourage active, engaging, and sustained participation in ENoP conversations. These findings provide the foundation for proposed guidelines that aim to enhance participation in knowledge sharing within such networks. This paper thus extends the existing body of knowledge by offering a detailed analysis of participation dynamics in ENoPs, particularly within the context of closed networks that are crucial for knowledge development, exchange, and dissemination (Allen, James and Gamlen, 2007).

The rest of the article is organized as follows: Section (2) provides a literature review on participation issues; Section (3) introduces the methodology; Section (4) focuses on applying the methodology to a real case; Section (5) highlights the findings of the case studied; and finally, Section (6) discusses the learnings from the proposed methodology and its application to the case, offering both theoretical and practical implications for enhancing participation in professional networks.

2 Literature review

2.1 Participation in Social Networks

Participation in social networks has been defined by user activities (Krasnova, et al., 2008) over time. The research on this matter includes those on Question–Answer networks such as Stack Overflow (Pudipeddi, Akoglu and Tong, 2014) and studies on continuant knowledge sharing (Cheung and Lee, 2007) and user activity lifespan (Yang, et al., 2010) in professional virtual communities. Factors have been found that influence continual participation, such as reciprocity, helping others, self-efficacy (Cheung, Lee and Lee, 2013), contribution attitude (He and Wei, 2009), and trust (Zhang, et al., 2010).

A branch of research focused on social networks with interactive messaging through conversations such as Yahoo Answers (Dror, et al., 2012), and not on non-interactive, concurrent, and instant messaging such as chat rooms. These *conversation-based networks* focus mainly on conversations as a group of messages about a certain topic and include many conversations in parallel. In contrast, in message-based networks, messages are all in a shared section regardless of the topics, and all users can reply to any message or post a new one. The widespread use of message-based networks for informal interaction (Carpenter and Green, 2017) further motivates researchers interested in this type of network.

This study focuses on message-based ENoPs that are self-formed, self-organized, and not formally managed by any association or organization. Approximately

90% of learning in social networks is informal (Jarrahi and Sawyer, 2013), and informal social media platforms are more favorable and influential on knowledge sharing (Kwayu, Abubakre and Lal, 2021). The case selected for the study is active in the health industry and focuses on the breast cancer treatment. It consists of about 500 medical specialists in the field, including surgeons, pathologists, and radiologists.

Participation has been measured in the literature in different ways: (1) the quantity of shared knowledge has been mostly considered as the level of participation (Guan, et al., 2018), (2) the quality and quantity of shared knowledge (Sedighi, et al., 2016), and (3) the perceived participation level (Yang and Lai, 2011). This paper measures participation by analyzing different user activities such as posting questions and cases; answering questions; sharing relevant information, experience, and knowledge; and discussing the issues raised. The network log is used for this purpose where each message is considered as a record in the dataset.

2.2 Conversation

In studies of participation in social networks, the unit of analysis varies. A significant number of studies consider the user from different aspects as the unit of analysis: user behavior (Bornfeld and Rafaeli, 2019) and user motivation (Liu and Chen, 2018). Others focus on the network as the unit of analysis; networks are compared based on their characteristics (Koh and Kim, 2004), content quality (Pang, et al., 2020), and resiliency and lifespan (Garcia, Mavrodiev and Schweitzer, 2013). Studies that analyze conversations focus primarily on conversation-based networks; characteristics of question–answers (Correa and Sureka, 2014), favorite hashtags and topics (Hafeez, et al., 2019), and learning and gaining knowledge from conversations (Ziegler, Paulus and Woodside, 2014). Yet, little has been done to analyze the details and structures of conversations in message-based networks where conversations are not easily and readily distinguished. As conversations are the platform of knowledge sharing and key indicators of participation in specialized expert networks, this paper considers *conversations* as the main unit of analysis based on which an analysis methodology is proposed. The two chosen perspectives on the nature of conversations are introduced in the following sections.

2.2.1 Macro Perspective—External Features of Conversation

The macro perspective perceives conversations, which may include numerous messages within, as entities with certain features such as the conversation topic and initiator (Figure 1). This perspective looks at the conversation from the outside and compares it with others.

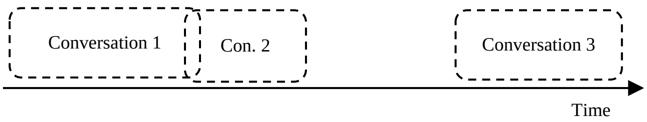


Figure 1. An outside view of conversations
(*Source*: Own elaboration)

The macro features, analyzed in question–answer networks, are question length, tags, votes (Ponzanelli, et al., 2014), feedback (Bornfeld and Rafaeli, 2019), date (Dror, et al., 2012), content quality, user reputation (MacLeod, 2014), and question topics (Wang, 2013).

Besides, macro features that relate to the way questions or posts are expressed influence user engagement, such as the clearly phrased questions, call-outs, and acknowledgment of responses (Wilen, 1991), and "how," "why," and "what" questions that encourage deeper thought and have a positive effect on achievement in general (Hussin, 2006). An overview of macro measures found in the literature is depicted in Table 1: they are called *conversation measures*.

2.2.2 Micro Perspective—Internal Features of Conversation

The micro perspective complements the macro perspective as it looks at a single conversation independently, focusing on the internal structure of a conversation (Figure 2), e.g., messaging time interval, participants, and length of messages.

Table 1. Conversation measures
(*Source:* Authors' own research)

Measure	Description	Modified from
Initiator rank in order of previous experience/participation	The initiator's rank with respect to others based on the total number of messages posted in a network	Wasko and Faraj, 2005
Initiator role	The initiator's role in a network, i.e., admin or member	Hafeez, et al., 2019
Initiator total no. of messages	The total number of messages the initiator has sent	Pudipeddi, Akoglu and Tong, 2014
Initiator total no. of conversations	The total number of conversations in which the initiator has been involved	
Initiator gender	---	Dror, et al., 2012
Time from the first message in the network	The time interval between an initiator's first message in a network and the last	Hafeez, et al., 2019
Date and time of the first message of the conversation	Date and time of the initiator's first message in a conversation	Dror, et al., 2012
Topic	The topic of conversation	Hafeez, et al., 2019
Question or statement?	Indicates whether the first message in a conversation is stated as a question or not	Campbell and Mayer, 2009
Question word	Indicates the type of question posted in the first message in a conversation	Zaib, et al., 2021
Completeness and clearance	The extent to which the information provided by the initiator to explain the question is clear and complete (based on text, references, attachments, and/or pictures)	Arguello, et al., 2006
Formal or informal	The formality of the first message of a conversation	Joyce and Kraut, 2006
Calling-out	Indicates whether the initiator specifically invites or names individuals to participate in a conversation	Wilen, 1991
Acknowledgment and feedback	Indicates acknowledgments and feedback in conversation messages, e.g., "like," "thank you," emoji	Bornfeld and Rafaeli, 2019

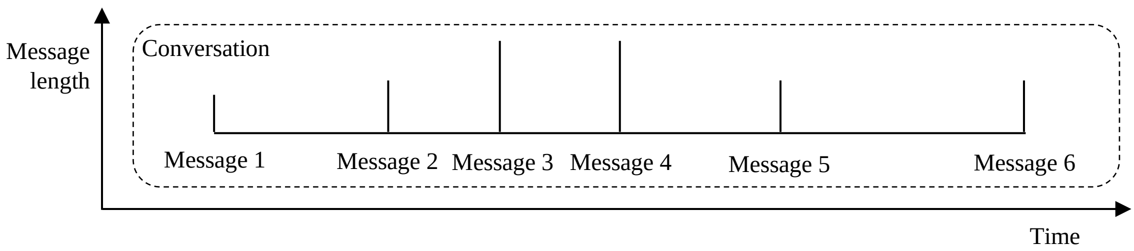


Figure 2. An inside view of conversations
(*Source*: Own elaboration)

Examples of micro-feature analysis are few; they include the analysis of timing and structure of comments and replies to the posts in public social networks such as Twitter (García-Peñalvo, et al., 2015), and response time and time-ordering of answers in question–answer networks such as Stack Overflow (Anderson, et al., 2012). The measures reported in the literature are depicted in Table 2; they are called *participation measures.*

Table 2. Participation measures
(*Source*: Authors' own research)

Measure	Description	Modified from
No. of messages	The number of messages in a conversation	Guan, et al., 2018
No. of participants	The number of users (specialists) who participate in a conversation	de Laat, 2002
Average message length	The average number of characters in a message per conversation	Hafeez, et al., 2019
Messaging average time interval	The average time interval between messages per conversation	Anderson, et al., 2012
Duration of a conversation	The time difference between the first and last message of a conversation	Hafeez, et al., 2019

Social network analysis (SNA) focuses on features of social structures and relations within a given network (Scott, 1988) and provides information on the activity level of the individual members, along with the overall activity of the network (Stewart and Abidi, 2012). Some SNA measures, reported in previous research works, are categorized here in conversation measures [degree, closeness, betweenness, size, indegree, outdegree, eigenvector, reach (two-step out), reach-efficiency, and MICMAC] (Wasserman and Faust, 1994) and in participation measures (average degree of the participants in a conversation) (Ponzanelli, et al., 2014). To analyze social network elements in a conversation in this study, participants are considered as the actors (nodes), and the messages between the initiator of a conversation and other participants are considered as the relational ties (edges). Figure 3 depicts a sample interaction structure occurring in a conversation.

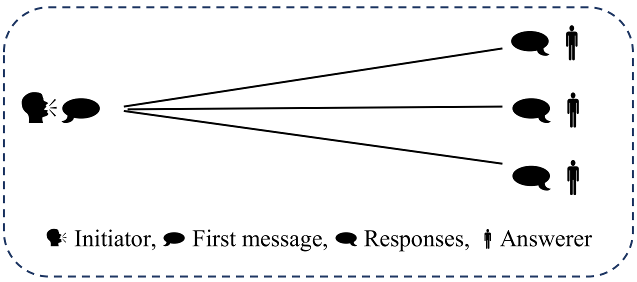


Figure 3. Social network elements in a conversation
(*Source*: Own elaboration)

2.3 Participation Analysis Methods

Several theories have been used to analyze participation in ENoPs as described above, varying from theories in information system literature such as expectation confirmation theory (Cheung, Lee and Lee, 2013) to theories embedded in psychology literature such as the theory of reasoned action (He and Wei, 2009). The methods deployed vary from applied qualitative research methods (Hashim, Ahmad and Shahranee, 2015) to data analysis algorithms such as social network analysis (Wasko and Faraj, 2005) and classification algorithms (Dror, et al., 2012). To the authors' knowledge, however, few, if no, studies focus on closed, informal, and message-based ENoPs for which this paper proposes a methodology for participation analysis at the conversation level. The proposed methodology, by focusing on conversation as the main platform of knowledge creation and knowledge sharing, innovatively measures and analyses the actual participation of experts.

3 The Proposed Methodology

Adopting the data science process (O'Neil and Schutt, 2013), this paper proposes an exploratory data analysis methodology for participation analysis at the conversation level within ENoPs. It should be noted that investigator triangulation, characterized by involving different investigators, is used to balance out the subjective influences of individuals (Flick, Kardorff and Steinke, 2004), in design, development, and evaluation processes.

The main processes are Network Assessment, Network Data Processing, Network Data Analysis, and Implications Assessment. Each process and its sub-processes are described in Figure 4.

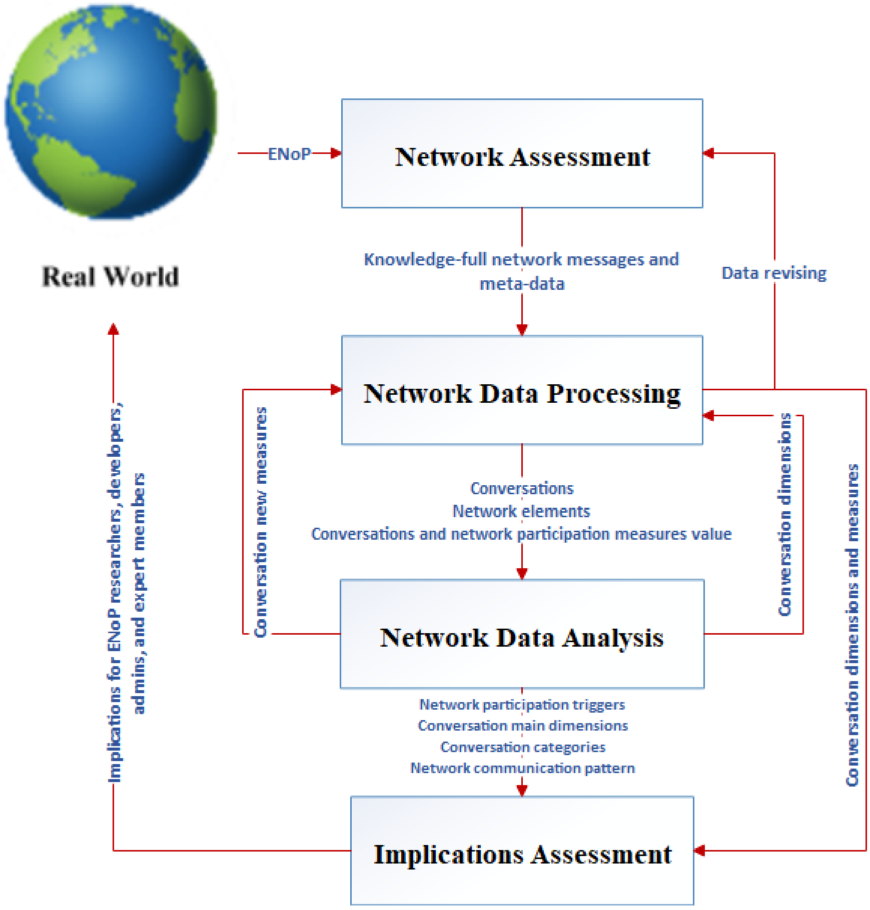


Figure 4. Data analysis methodology for participation in ENoPs
(*Source*: Own elaboration)

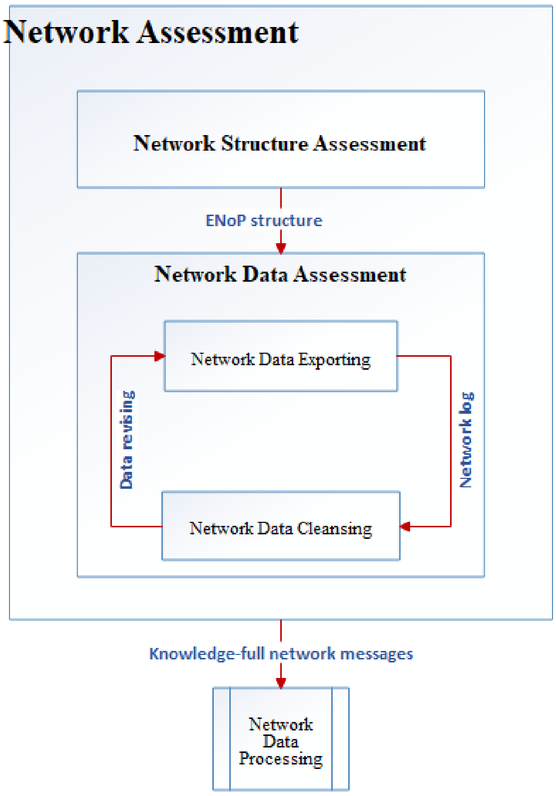


Figure 5. Network assessment process
(*Source*: Own elaboration)

3.1 Network Assessment

The first process, as depicted in Figure 5Figure , starts from the raw data it receives from the network operation as input and runs the following two sub-processes: structure assessment and data assessment. The outputs are the ENoPs structure, network logs, and its knowledge-full content.

3.1.1 Network structure assessment

Given the raw data of communication logs, the network structure is analyzed and characterized for different attributes [such as purpose, formalization, composition (experts/non-experts), boundary (closed/open), size of the community, geographical dispersion] and network elements [including participants and messages, their relations, and form of messaging]. A description of the network structure is the output of this sub-process.

3.1.2 Network data assessment

This includes data exporting and cleansing sub-processes. First, raw data for the period of the study are extracted from the network logs and translated into an analyzable format in which each message has these attributes: content, type (text, photo, or document), time, date, sender, and if it is forwarded or replied to, from who or to whom. The edited network log is then cleansed from knowledge-less messages, i.e., general ones that don't contain knowledge are eliminated and, if needed, the data are reformatted. The outputs are knowledge-full messages that contain knowledge, together with their meta-data (Figure 5).

3.2 Network Data Processing

Knowledge-full messages and their meta-data are the input to this stage. Figure 6 depicts the sub-processes which these data go through: Exploratory Data Analysis, Conversation and Network Elements Extraction, and Conversation and Participation Measurement.

3.2.1 Exploratory data analysis

Exploratory data analysis is a numerical-graphical detective work. It is a philosophy of data analysis where the researcher examines the data without any preconceived ideas in order to discover what the data can tell about the phenomena being studied (Tukey, 1977). It helps to gain familiarity with the characteristics of conversations and network elements of the network under study. To do such analysis, the practice of "eyeballing statistics" is employed, i.e., looking at a set of data and making estimates of statistical values without carrying out statistical calculations (Byrne, 2016).

3.2.2 Conversation and network elements extraction

For the outcome of exploratory analysis, conversations and interactions among experts and network nodes are extracted using the three sub-processes depicted in Figure 6.

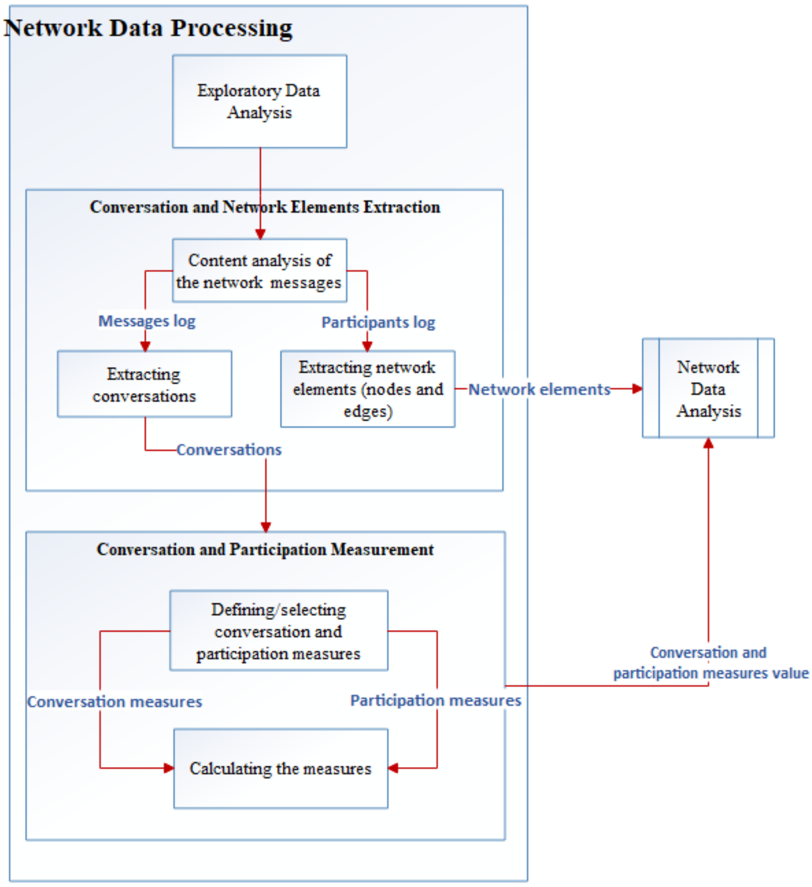


Figure 6. Process of network data processing
(*Source*: Own elaboration)

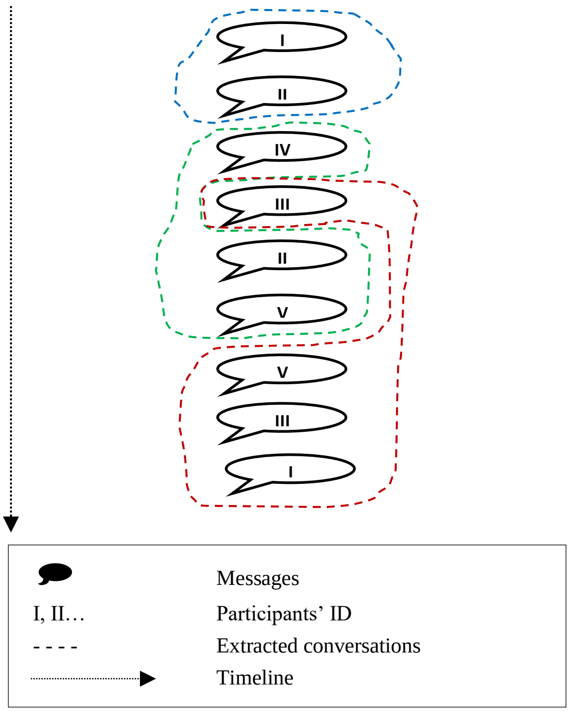


Figure 7. A sample structure of message-based conversations
(*Source*: Own elaboration)

Content analysis: Content analysis is applied to the messages in cleansed network logs with two goals: to extract conversations and to uncover the network interaction structure, i.e., nodes and ties found in interactions amongst nodes. Investigator triangulation is needed to validate the results of the analysis for both.

Extracting conversations: Conversations are identified and separated using the possible border signs found in the messages exchanged. Table 3 shows proposed signs for this purpose: these signs are identified in content analysis of the network log and validated by investigator triangulation.

Network elements extraction: Network elements, i.e. nodes and edges, are extracted from network logs based on the interaction structure between the initiator of a conversation and other participants in the conversation in Figure 3.

Table 3. Conversation possible border signs
(*Source*: Authors' own research)

Conversation Border signs	Explanation	Sample
Initiation words	Words with which a conversation begins	"Hello," "Dear," "Please look at the files," "Good day"
Files	The inclusion of files can indicate a new topic	---
Content	Changing the topic	---
Messages' connections	Replies and references to previous messages in another conversation (It shows this message is a part of the other conversation and in the border of that conversation.)	The connection between the first message of participant III and the second message of participant V in Figure 7.
Closure words	Acknowledgment and feedback	"like," "thank you," emoji

3.2.3 Conversation and participation measurement

The conversations extracted in the previous step are the input to this process which consists of two sub-processes including defining/selecting domain-specific measures of conversation and participation and calculating those measures. Triangulation of experts should be used to validate the obtained values from the measurement sub-process. This study adds the conversation measures in Table 4 to the ones found in the literature.

Table 4. Proposed conversation measures
(*Source*: Authors' own research)

Measure	Description
Initiator field	Professional field of the initiator
Initiator city	---
Initiator country	---
Holiday?	If the start date of the conversation is a weekend/holiday or not
Date and time of the last message of the conversation	Data and time of the last message in a conversation
The time interval from the previous conversation	The difference between the start dates/times of one conversation and the previous one
The time interval from the next conversation	The difference between the start dates/times of one conversation and the next

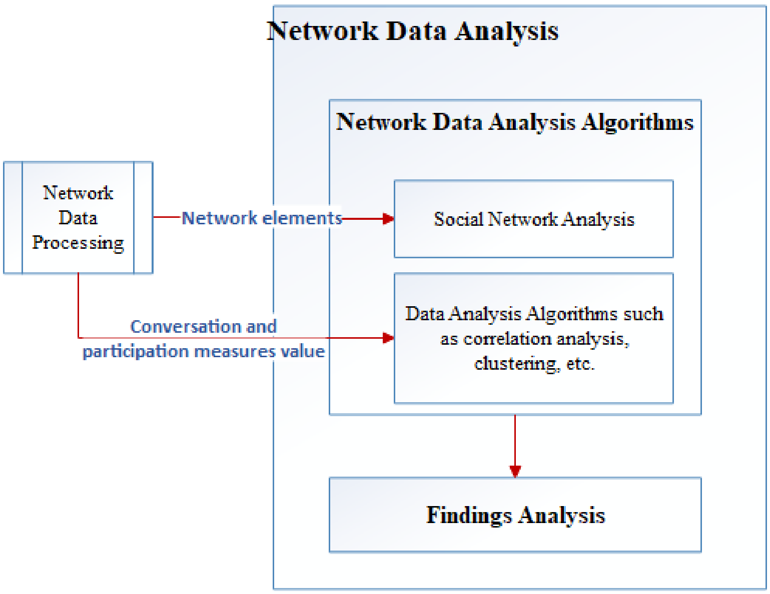


Figure 8. Network data analysis process
(*Source*: Own elaboration)

3.3 Network Data Analysis

Once the conversation structure and network internal structure are identified, and conversation and participation measures are obtained, the data analysis process involving two sub-processes shown in Figure 8 is applied: Network Data Analysis Algorithms and Findings Analysis.

3.3.1 Network data analysis algorithms

The nature of data, context, network structure, and the objective of analysis are used at this stage of the proposed methodology to select and determine which algorithms to deploy, e.g., social network analysis, correlation analysis, clustering, classification, and regression.

3.3.2 Conversation and participation measurement

It includes obtaining values and knowledge from the application of selected algorithms and the presentation of findings to provide insights into the network of practice studied.

3.4 Implications Assessment

In this step, information and knowledge obtained from the network, conversation, and participation analysis are used to provide theoretical and practical advice for the success of the ENoP under study and help overcome obstacles to the effectiveness of performance and continuity of services to society.

4 Case Study: Application of the Methodology

The case being studied is an ENoP concerned with breast cancer treatment, named the Breast Cancer Management Group (BCMG), a professional and closed network, dispersed geographically, and connected informally through a message-based social network on the Telegram platform. BCMG has been an active virtual community since November 2015, with an average of 30 messages a day and approximately 500 participant specialists in breast cancer treatment including surgeons, pathologists, oncologists, and radiologists. BCMG has been chosen as the case for this study due to its longevity, the knowledge-full specialties of breast cancer treatment, the compatibility of the features of this network with the proposed method, and the availability of data. The expert participants are from major specialized centers of treatment and health services across the country; they are well-recognized in the domain of expertise and contribute significantly to the well-being of society. There are seven members who co-play the administrator and organizer roles, including membership management.

The application of the proposed methodology to this specialized network of practice will be elaborated in the following sections. Networks of this type are invaluable intangible assets that contribute significantly to the return to health for those suffering from severe diseases; thus, insights obtained from the attributes, activities, and dynamics of their operations are very useful for learning and promoting networks of a similar type in various domains of serving societies.

4.1 Network Assessment

The Network Assessment determines the network structure, prepares the data and meta-data in the network logs for analysis, and inspects the network data to determine how it can best be analyzed.

4.1.1 Network structure assessment

BCMG specialists participate in different conversations of interest by instant messaging, as demonstrated in Figure 7. Participants can initiate a conversation at any time, and multiple conversations can run in parallel. Conversations are not clearly separated and may overlap. Figure 9 provides a screenshot of consecutive messages.

Figure 9. A screenshot from the BCMG network (*Source*: Own elaboration)

4.1.2 Network data assessment

This includes the following activities:

Network data exporting: The communication log used in this study covers January to February 2018. The sample includes 1000 messages with the participation of approx. 100 specialists in breast cancer treatment, with numbers of surgeons and onco-surgeons at approx. 70%, clinical/radiation oncologists approx. 15%, radiologists approx. 10%, and other related fields like pathologists or general practitioners, approx. 5%.

Network data cleansing: To clean data, knowledge-less messages like "hello," "thank you," and emojis are eliminated from the data set.

Two independent specialists in the breast cancer treatment perform the same type of content analysis on the same sample and discuss this to validate the outcome.

4.2 Network Data Processing

4.2.1 Exploratory data

Exploratory analysis of the clean raw data using eyeballing statistics in the sample shows that 80% of participation is done by 26% of participants. Figure 10 presents the trend of participation of 25% of the most active participants with more than ten messages in total over time. These results suggest that there are triggers that initiate participation and participant engagement.

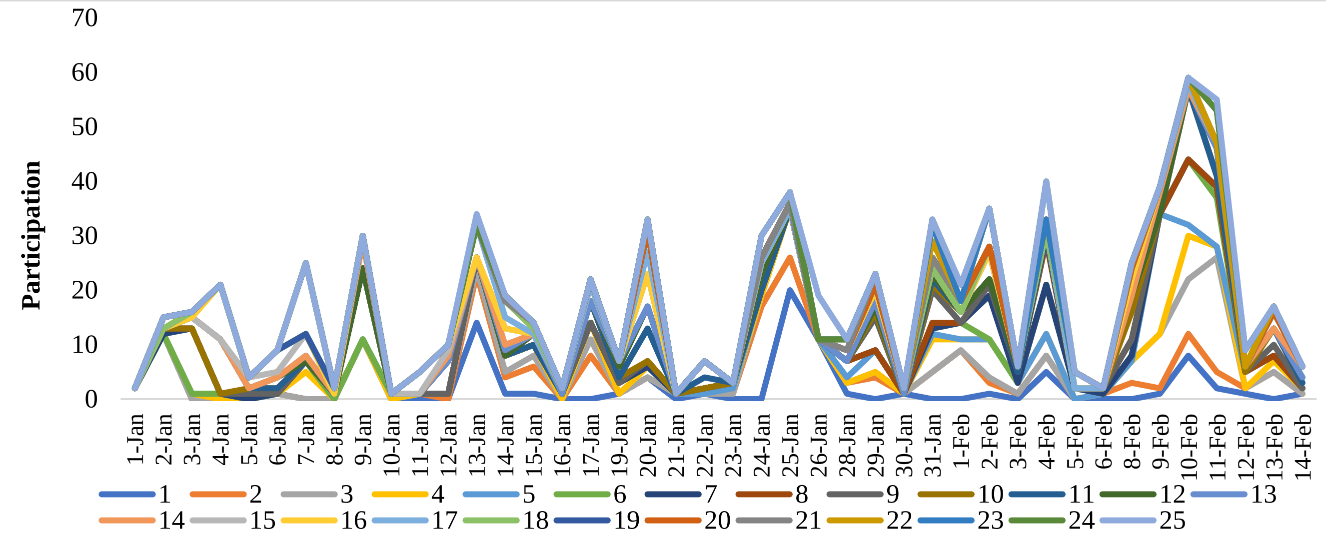


Figure 10. The trend of participation for 25% of the most active participants
(*Source*: Authors' own research)

Table 5. Border signs identified in the BCMG
(*Source*: Authors' own research)

Conversation Border signs	Sample
Initiation words	"Hi colleagues," "Dear colleagues," "Please look at the files," "Good day," "Please consider my patient case," "A patient…"
Files	Photos containing MRI and CT scans or files with laboratory and pathology reports
Content	Messages referring to treatment, diagnosis, or screening
Messages' connections	Replies and references to the previous messages of the conversation
Closure words	"Like," "thank you," emoji

4.2.2 Conversation and network elements extraction

This includes the following activities:

Extracting conversations: Considering domain-specific features of communication, the conversation border signs are adapted and proposed as in Table 3, presented in Table 5, and used to identify and separate conversations in the sample. For validation, two independent specialists in breast cancer treatment performed the same type of content analysis on the same sample, then discussed, and validated the outcome, namely, the identification of 51 conversations in the sample.

Network elements extraction: Content analysis is applied to the network log: as a result, 79 actors and 190 ties are identified and validated by the same two independent specialists mentioned above, following the same procedure.

4.2.3 Conversation and participation measurement

This is conducted using measures introduced in Tables 1–4 and then validated by the same specialists mentioned above.

4.3 Network Data Analysis

This step of the proposed methodology provides capacity and room for the intervention of a data analytics expert to identify and apply relevant and suitable data analysis algorithms and to analyze the findings of the application process. Accordingly, the techniques selected for the analysis of the case at hand are presented below.

4.3.1 Network data analysis algorithms

Figure 11 shows the analytical algorithms chosen and applied to the case, such as social network analysis, principal component analysis, correlation analysis, and clustering.

Social network analysis: The network structure is determined through analysis of the elements, namely 79 actors and 190 ties, input from the Network Data Processing step. The values of the social network measures are then measured. The obtained communication pattern will be described in the next section.

Correlation analysis: In this case study, correlations between all conversation measures and participation measures, as depicted in Tables 1–4, are analyzed to identify potential associations and participation triggers. The obtained measures (variables) are of continuous, ordinal, and nominal types, where different correlation coefficients are used, like Pearson's correlation coefficient *r* for the linear relationship between two continuous variables, Spearman's correlation coefficient for the monotonic relationship between two continuous and ordinal variables, and Eta coefficient for the association between two continuous and nominal variables.

Clustering algorithm: "Clustering" is an unsupervised classification of entities (observations, data items, or feature vectors) into groups called "clusters" (Jain, Murty and Flynn, 1999). It is used in this case study to detect and analyze conversation categories. Several clustering algorithms exist (Chicco, 2012); K-means is used in this work to analyze connections between participation measures, i.e., No. of messages, No. of participants, Message average length, Messaging average time interval, Duration, and Participants average degree. To this purpose, data are normalized and scaled to [0, 1]; the k-means clustering algorithm requires the number of clusters, k, to be specified in advance. The cluster validity index (CVI) is thus calculated to optimize the number of clusters. The CVI used in this paper is the Davies–Bouldin index (DBI) (Davies and Bouldin, 1979). The optimal number of clusters is determined based on the minimum index value, which equals five in this case (Figure 12); these five clusters resulting from the k-means algorithm are then introduced and compared.

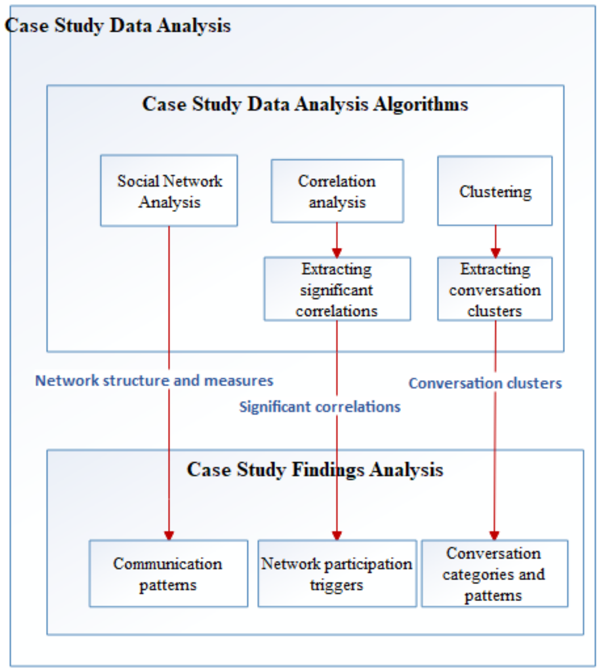


Figure 11. Data analytical processes applied to the case
(*Source*: Own elaboration)

Figure 12. Davies–Bouldin index (DBI) for k clusters
(Source: Authors' own research)

5 Case Study: Analysis and Results

The application and customization of the proposed methodology for studying BCMG and application to the sample data provide useful information on participation activities and the interaction structure of participants, which will be described and illustrated in this section.

5.1 Social Network Analysis

Social network analysis of the BCMG conversations reveals the network structure of the sample, as illustrated in Figure 13.

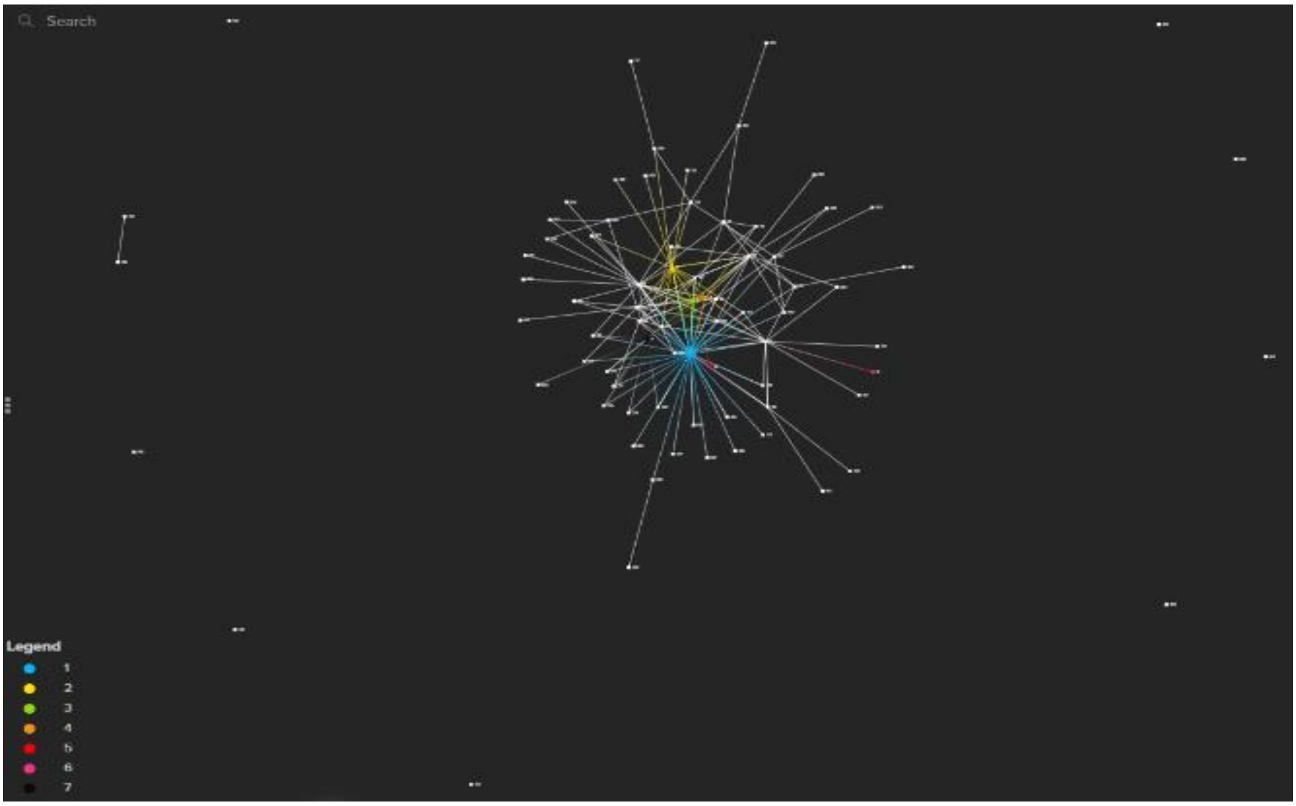


Figure 13. The network structure of the BCMG sample
(*Source*: Authors' own research)

The result of this analysis, as partially shown in Table 6, reveals that this network is fairly well connected: high centrality measure scores indicate that members can readily connect to each other.

The distance betweenness scores, however, shows that the network depends on a relatively small set of members who transfer knowledge across the network.

Table 6. Social network analysis results for 25% of the most active participants
(*Source*: Authors' own research)

Participant	Degree	Closeness	Between-ness	Size	Indegree	Outdegree	Eigenvector	Reach	Reach-efficiency	MICMAC
1	63	0.64	0.42	35	63	63	0.12	0.82	0.02	0.66
2	25	0.53	0.15	19	25	25	0.07	0.76	0.04	0.95
3	18	0.47	0.02	11	18	18	0.06	0.72	0.07	0.86
4	15	0.48	0.03	11	15	15	0.05	0.77	0.07	0.89
5	8	0.41	0.00	6	8	8	0.04	0.56	0.09	0.77
6	1	0.31	0.00	2	1	1	0.00	0.19	0.09	0.92
7	21	0.52	0.05	19	21	21	0.05	0.70	0.04	0.82
8	17	0.44	0.05	14	17	17	0.03	0.42	0.03	0.86
9	17	0.49	0.09	15	17	17	0.03	0.68	0.05	0.84
10	16	0.47	0.05	13	16	16	0.04	0.65	0.05	0.89
11	24	0.53	0.15	19	24	24	0.06	0.75	0.04	0.79
12	9	0.45	0.01	9	9	9	0.02	0.67	0.07	0.86
13	6	0.42	0.04	7	6	6	0.01	0.53	0.08	0.97
14	3	0.36	0.00	4	3	3	0.01	0.35	0.09	0.67
15	5	0.42	0.03	6	5	5	0.01	0.61	0.10	0.75
16	7	0.44	0.00	7	7	7	0.02	0.67	0.10	0.72
17	6	0.39	0.02	7	6	6	0.01	0.43	0.06	0.82
18	8	0.41	0.04	6	8	8	0.03	0.53	0.09	0.72

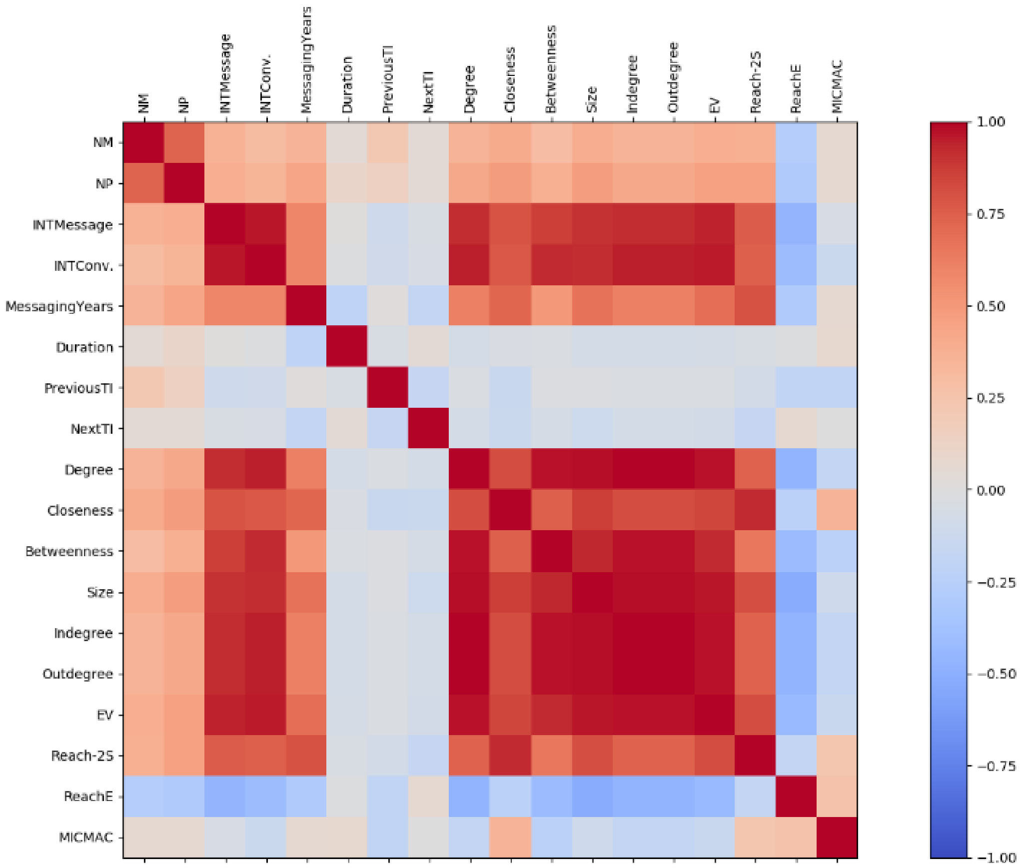


Figure 14. Heatmap of Pearson correlation analysis result
(*Source*: Authors' own research)

5.2 Correlation Analysis

The correlation analysis of all conversations shows significant associations between all conversation measures and participation measures (Tables 1–4). Significant associations are reported, like Pearson's correlation coefficient *r* for scale variables which is shown in Figure 14.

The researchers conduct the analysis assuming that [a] correlation is significant at the 0.01 level (2-tailed) and [b] at the 0.05 level (2-tailed). The results indicate that social network measures of a conversation initiator such as degree, closeness, and betweenness are significantly correlated with the number of messages (0.358[a], 0.399[a], 0.290[b]) and participants (0.421[a], 0.477[a], 0.378[a]) in the same conversation (measures of participation). In addition, a conversation initiated by a central participant is correlated with a lower time messaging time interval in the very same conversation (-0.322[b]).

Duration of membership and the activity rank of a conversation initiator are significantly correlated with the number of messages (0.353[b], -0.527[a]) and participants (0.437[a], -0.467[a]) in the same conversation.

The role of a conversation initiator such as administration of the network is also relatively correlated with the number of messages (0.262) and participants (0.443) in the conversation. The role of a conversation initiator is also correlated with the centrality of other participants in the conversation (0.494).

The time distance of a conversation from the previous one is correlated with the number of messages (0.350[b]) exchanged in the conversation.

From the "acknowledgment and feedback" perspective, there is a correlation between acknowledging and giving feedback in a conversation and the number of messages (0.524) and participants (0.301) in the conversation.

There are no clear and significant correlations between participation in a given conversation and the following measures of conversation initiation: initiator gender, calling-out, conversation start time and date, time distance from the next conversation, topic, and the expression type as question or statement, question word, completeness and clearance, and being formal or informal. Correlations between certain measures, such as the city and the field of expertise, have been ignored due to the lack of homogeneity.

5.3 Data Clustering

The optimized clustering of BCMG conversations using the K-means algorithm introduces the specifications of each cluster (Figure 15 and Figure 17). In addition, Figure 16 shows 20 combinations of the six conversation measures for the five clusters in a 3D scatter plot format; each cube considers three out of the six measures to form a cube and provides an overall view of the five clusters. To be specific, the characteristics of the five clusters are on average as shown in Table 7.

Table 7. Characteristics of the five clusters
(*Source*: Authors' own research)

Cluster	# Messages	# Participants	Degree	Duration (days)	Messaging time interval (days)	Message length (characters)
1	10	4.6	7.9	12	1.8	106
2	30.5	10.1	14.9	1.4	0.06	190.8
3	16.8	5.6	22.5	0.6	0.04	113.6
4	3.6	2.1	16.6	0.8	0.4	226.1
5	5.6	2.4	6.5	0.3	0.07	119.4

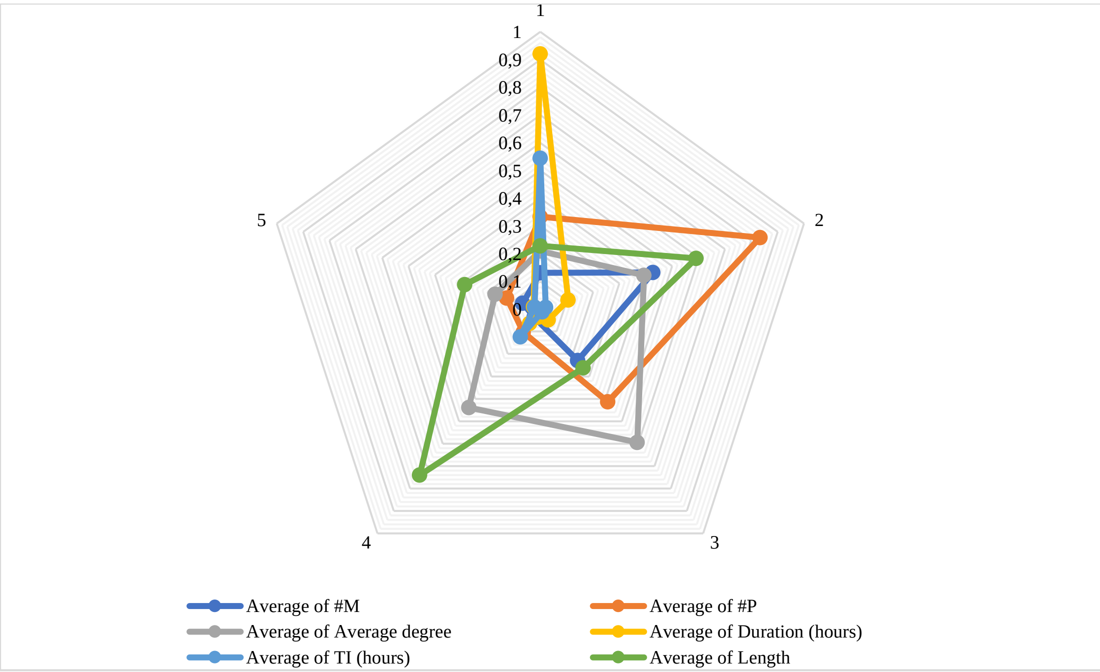
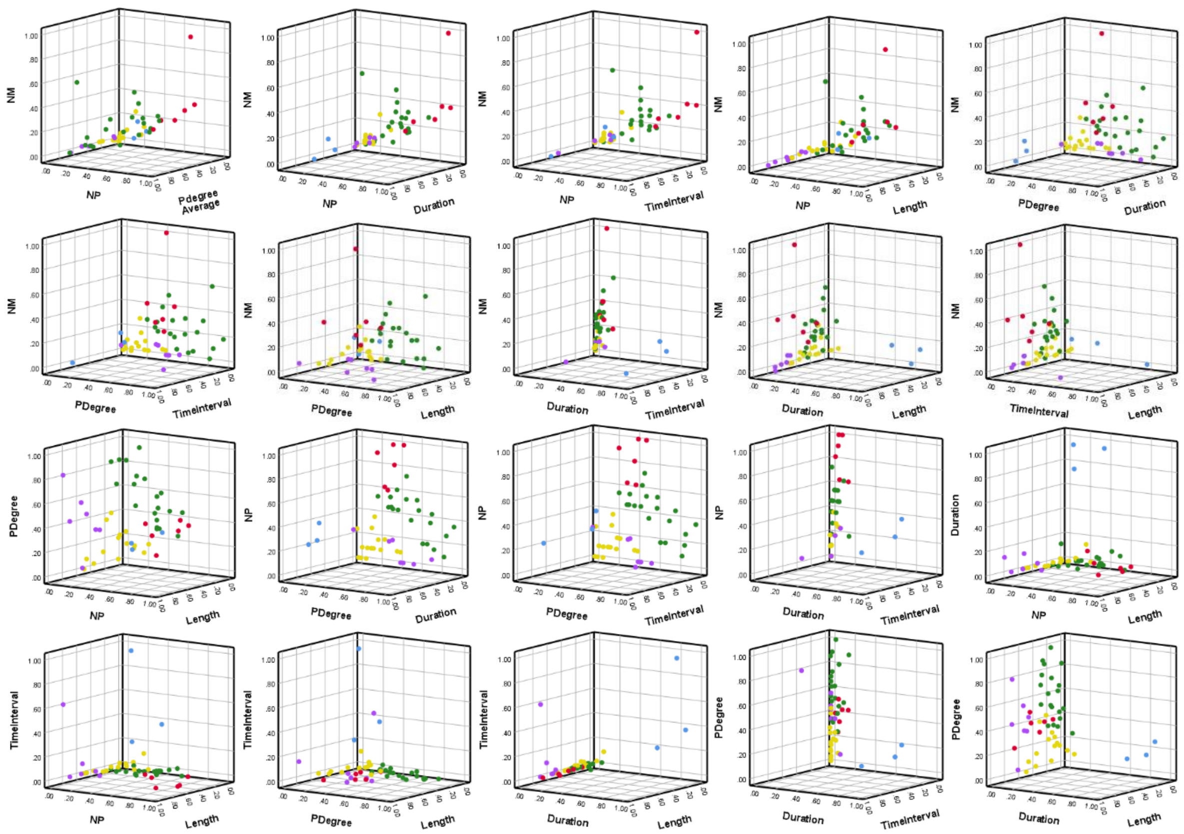


Figure 15. Radar chart of clusters' characteristics
(*Source*: Authors' own research)



Cluster Number	1 🔵	2 🔴	3 🟢	4 🟣	5 🟡

Figure 16. 3D scatter plots of six measures of participation
(*Source*: Authors' own research)

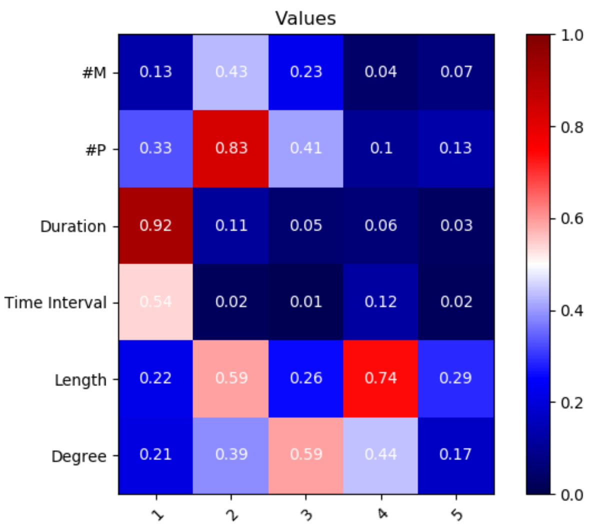


Figure 17. Heatmap of cluster characteristics
(*Source*: Authors’ own research)

In this study, IBM SPSS Statistics version 26 is used for correlation analysis and clustering analysis. The same version of SPSS is also used for comparing clusters. Python is employed to generate both of the heatmaps included in the paper, and the code is available at this link. We understand the importance of data availability for research reproducibility. However, we are committed to data privacy, so we provided anonymized raw data to protect the participants' information.

6 Findings and Discussion

6.1 The Methodology

Several studies have proposed network participation analysis methods (Hashim, Ahmad and Shahranee, 2015), algorithms for conversation extraction (Belkaroui, Faiz and Elkhlifi, 2014), and conversation analysis measures (Bornfeld and Rafaeli, 2019).

These investigations delve into various aspects of conversation-based networks, exploring characteristics of question–answers (Correa and Sureka, 2014), and Twitter conversations analysis (Rehm, et al., 2021). Although message-based networks are widely used for informal interaction (Carpenter and Green, 2017), they remain relatively unexplored.

This paper goes a step further and proposes a comprehensive and detailed conversation-based data analysis methodology for message-based ENoP participation, including:

- a specific conversation extraction method;
- a specific social network elements extraction method;
- a set of macro and micro measures with which to determine conversation and participation.

6.2 The Case Study

The application of the proposed methodology to analyze the BCMG has deepened our understanding of the influence of social network structures, participation triggers and measures, and conversation categories.

Social network structure: The analysis reveals the critical role of a few central members within the network. Knowledge flows through these pivotal members within the network, and their high level of participation is vital to the ENoP's continuant achievements.

Participation triggers: There is a significant correlation between conversation initiator measures and participation measures. This finding aligns with previous studies that show that engagement in knowledge sharing is high when network centrality is high (Reinholt, Pedersen and Foss, 2011): individuals with higher levels of network centrality contribute more to ENoPs (Wasko and Faraj, 2005).

The strong association found in this paper between the duration of membership and the activity level of conversation initiator with participation is consistent with a previous work on Stack Overflow, which studied the correlation of participation with membership duration, activity level, and being-known level of participants, their participation (MacLeod, 2014) and their lifespan (Pudipeddi, Akoglu and Tong, 2014) in the network. The association between the role an initiator plays in the network with members’ participation also shows that a conversation initiated by an active, central, or well-known participant is strongly correlated with higher participation of other members and faster message exchange. This is in line with studies on the use of Stack Flow (Anderson, et al., 2012).

Another case-specific finding of this study shows that the timing of conversation initiation matters. If a conversation is started close to another ongoing conversation, the new one runs the risk of being overwhelmed and ignored, with less participation as a consequence.

The association of acknowledging and feedback giving with members' participation found in this work is in line with previous reports. Feedback affects newcomers' motivation in Wikipedia (Zhu, et al., 2013) and newcomers' retention in Stack Overflow (Bornfeld and Rafaeli, 2019). Feedback encourages further posting in the Stack Exchange Math community (Tausczik and Pennebaker, 2012) and results in a longer user lifespan (Yang, et al., 2010).

The two measures of conversation topic and expression were found to have no influence on participation in this paper. These are in contrast to certain studies where the content topic has been shown to have a significant effect on conversation participation (Wang, 2013). Rhetorical form, in which a person frames a question, is likely to influence how others respond to it: e.g., questions are more likely to get a response than other types of speech forms (Arguello, et al., 2006). This discrepancy is a topic for future research. However, the results of this research are consistent with a study on expression that found no significant correlation between rhetorical strategies and predicting answer outcomes (Harper, et al., 2008).

Conversation categories: This study categorizes conversations into five distinct clusters, each with its own characteristics and message patterns. These characteristics are relatively compared in Figure 18.

Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
• Medium participation • Medium active members involvement • Shallow answering	• High participation • Medium active members involvement • Long conversations • Fast answering • Zigzag pattern • Debate/ conflicts	• Medium participation • High active members involvement • Medium length conversations • Fast answering • Zigzag pattern • Debate/ conflicts • Far from other active conversations	Low participation Medium active members involvement Medium length conversation	• Low participation • Low active participants • Short conversations • Close to other active conversations

Figure 18. Conversation clusters characteristics
(*Source*: Own elaboration)

The first category consists of conversations with the lowest number of participants, close to another active conversation, in which one participant is the main/only contributor (in a monologue) and questions are left unanswered. This category (cluster 5) is labeled "dead conversations."

The second category consists of conversations with low participation. They consist mostly of a short dialogue between two medium-active participants with a request and an answer. This category (cluster 4) is called "quiet conversations."

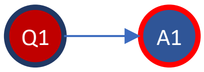
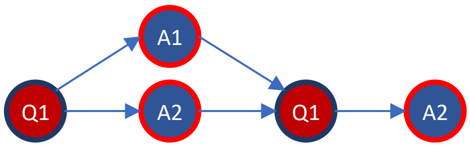
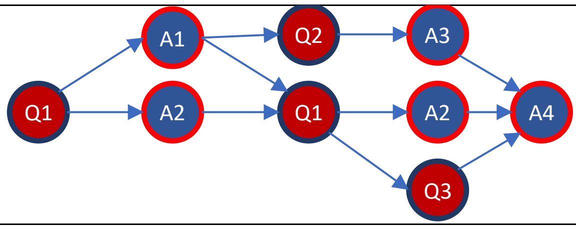
The third category includes a few conversations with medium participation and slow answering speed. They are mostly a polylogue between one participant with a request and more than one participant who answers. This category (cluster 1) is labeled "medium conversation."

Other conversations are discussions between more than a few participants. They often include a debate on different ideas and conflicts. The fourth category includes discussions with high participation of medium active members. These conversations progress in a zigzag pattern with fast messaging speed between several participants. This category (cluster 2) is labeled "crowded conversations."

The last category consists of discussion with a medium number of highly active participants. These conversations show a zigzag pattern and fast messaging speed between a number of central participants. This category (cluster 3) is named "dense conversations."

The two last categories of conversations are discussions with high participation which guide us on how to move from a lower to higher level of participation, e.g., having active participants and answering fast are shown as critical factors to reach a higher level of participation. Anderson, et al. (2012) obtained a similar result: a significant association between the asker's reputation and the answerers' reputation and also relationships between asker's reputation and answer speed. Table 8 briefly shows an overview of these categories, including internal patterns and messaging structures.

Table 8. Conversation Categories
(*Source*: Own elaboration)

Conversation Category	Label	Messaging pattern and structure
Monologue	Dead conversations	
Dialogue	Quiet conversations	
Polylogue	Medium conversations	
Discussion	Crowded conversations	

These findings hold significant implications for social network professionals, offering insights into designing knowledge platforms for collective problem-solving and collective and individual learning in informal virtual communities which are based on voluntary conversations. To ensure the continuity of ENoPs, monitoring systems can be developed to extract conversations, measure participation performance, and monitor interaction dynamics. The associations between variables identified in this work can inform the design of initiatives that encourage network members to increase their contributions when necessary. System developers can also benefit from these findings in designing conversation extraction algorithms.

In summary, this research contributes to the existing literature by introducing (i) an adaptive exploratory methodology for analyzing conversation-based ENoPs, (ii) well-defined conversation categories with attributes and measurements, (iii) participation triggers with associated measurements, and (iv) the successful application of this methodology to a real ENoP in the health industry.

7 Conclusion

This study on Electronic Networks of Practice with specific focus on understanding participation patterns, triggers, and conversation dynamics within the network contributes to the existing body of knowledge in following seven key aspects:

Methodology Advancements: We introduced an adaptive exploratory methodology tailored for analyzing conversation-based ENoPs. This methodology encompasses specific techniques for conversation extraction, social network element extraction, and a range of macro and micro measures for conversation and participation assessment. This enables researchers and practitioners to gain deeper insights into these complex networks.

Social Network Structures: This investigation highlighted the critical role played by a select group of central members within ENoPs. These central members serve as conduits for knowledge sharing, and their high levels of participation are pivotal for the continuity of effectiveness and success.

Participation Triggers: In this study, we identified and confirmed the significance of conversation-initiator measures in driving participation. This finding aligns with prior research, emphasizing the positive relationship between network centrality and engagement in knowledge sharing. Furthermore, this study underscored the importance of factors such as membership duration and activity level in influencing conversation initiation and participation.

Timing Matters: The influence of conversation initiation timing on participation levels was emphasized. Conversations initiated in close proximity to ongoing discussions were prone to being overshadowed and receiving reduced levels of participation.

Acknowledgment and Feedback: Acknowledgment and feedback mechanisms are found to have a positive impact on member's participation and underscore their importance in fostering active participation. These findings confirm earlier reports in various online communities.

Conversation Categories: Through a thorough categorization process, we classified conversations into distinct clusters, each characterized by unique attributes and messaging patterns. These categories, ranging from "dead conversations" to "dense conversations," offer valuable insights into the factors that facilitate higher participation levels.

Implications for Practice: The findings have significant implications for social network professionals keen to design knowledge platforms for collective problem-solving and learning. Knowledge gained from this research guides the development of monitoring systems that extract conversations, measure participation performance, and monitor interaction dynamics. Understanding the associations between various variables identified in this work enables practitioners devise initiatives to energize network members and promote contributions when needed. System developers can also leverage these insights to design more effective conversation extraction algorithms.

In summary, this research provided a holistic understanding of participation dynamics within conversation-based ENoPs by introducing a refined methodology, defining clear conversation categories, identifying participation triggers, and applying these insights to a real case in the health industry. In a world with an increasing role of collective knowledge to tackle complex multi-aspect problems surrounding us, from individual health to global climate change, this work equips researchers, practitioners, and professionals interested in enhancing knowledge sharing and collaboration within online professional networks.

8 Limitations and future research

While this study has shed light on several important aspects of ENoPs, certain limitations should be acknowledged. First, access to patient data and information disclosure is a very sensitive issue in the health industry and deserves close attention. Therefore, the researchers reached a nondisclosure agreement with the administrators and organizers of the network, according to which access to the data was limited and anonymized for research purposes. The highly specialized and detailed content of conversations prevented more precise typology.

Second, the generalization of case-related findings like associations between conversation measures and participation measures demands further investigation. Also, behavioral approaches to analyze participation can provide deep insights into motivating factors and barriers to active participation in ENoPs. Reasons behind non-participation in such networks and causal relations among variables affecting conversation and participation also need further research.

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