Investigating social network patterns within an empathic online community for older people

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ABSTRACT

In this paper, we study the social network structure of an online discussion board within SeniorNet, an empathic online community for older people. We apply Social Network Analysis (SNA) to analyse the communication patterns and relationships between members of the discussion board. In addition to looking at the structure of the exchanged messages within the discussion board as a whole, we also investigate associations between the communication content and the social network patterns. Our findings show distinct differences between the social network patterns of empathic and non-empathic communications. For example, members are more connected and closer to each other in the social networks that are based on empathic communication compared to non-empathic communication. Additionally, our results show that the type of empathic communication (e.g., different kinds of support) is linked to the social network structure within the discussion board.

1. Introduction

Scholars in the area of computer-mediated communication (CMC) have been increasingly interested in studying social interaction in online communities. Social Network Analysis (SNA) is a common method for investigating these settings and has been used in previous studies to analyze the position of individuals within online social networks (e.g., Paccagnella, 1998) and the overall structure of communication patterns within online communities (e.g., Zaphiris & Sarwar, 2006).

However, only few studies have so far focused on empathic online communities. Empathic online communities offer a place for people who experience similar life situations to exchange informational and emotional support (Preece & Ghozati, 2001). Current studies that have investigated empathic online communities (Pfeil & Zaphiris, 2007; Preece 1998, 1999a, 1999b) have mainly focused on the content of communication within the online communities, not taking into account the network of links and relationships that people form in these online communities. But what are the characteristics of the social networks of empathic online communities? Does the support that is being exchanged in these communities relate to specific network structures?

In our study, we aim to address these issues by investigating an empathic online community for older people. In recent years, the number of older people that use the internet is constantly growing. Studies show that in Britain and the US roughly a quarter of the population aged 65 and above is using the internet (Fox, 2004; Office of communication, 2006) and this number is estimated to increase further. Also, apart from searching for information, older people increasingly use the internet for communication purposes, e.g., for writing emails to friends and family members (Fox, 2004). Empathic online communities give older people the opportunity to interact with each other, which according to Czaja, Guerrier, Nair, and Laudauer (1993) has been found to have a positive impact on their quality of life. Furthermore, using the computer can help older people to stay active (Eilers, 1989). Work has already been done analyzing the content of the communication in empathic online communities for older people and their satisfaction with it (Pfeil & Zaphiris, 2007; Wright, 1999, 2000), but little has been done researching the compositions of online social network structures of empathic online communities for older people and the influence of the content of such online communication on the network structures (Zaphiris & Sarwar, 2006).

In a former study, we did a qualitative content analysis of the messages in the discussion board about depression within SeniorNet, an empathic online community for older people (Pfeil & Zaphiris, 2007). In our analysis, we realised that the content of the messages is only one aspect of the online community and in order to fully understand the activities within the discussion board we also need to investigate the social network structure and relationships between the members of the online community. In the current study we aim to build on the former findings and allows for a better understanding of communication and network patterns.
of empathic online communities. More specifically, this study aims to link characteristics of network structures to the content that the members of this empathic online community exchange (e.g., is supportive communication associated with a different network structure than factual communication?). This aim can be broken down into three more specific research questions:

1. Is the exchange of emotional communication content associated with specific characteristics of the social network structure opposed to factual communication content?

2. Are the two opposite components of empathic communication (seeking and giving support) associated with specific characteristics of the social network structure?

3. Are different kinds of support that people exchange in online empathic communities associated with specific social network characteristics?

Understanding the links between the communication content and the social network that is based on that communication can help us better understand the dynamics and the social network development in empathic online communities. Depending on the topic and content of the communication, different structures of social networks might emerge. This sheds light on the link between empathic communication in online communities and the connections that exist between the communicators.

The literature review gives a summary of the basic concepts of social network theory and addresses if and how Social Network Analysis (SNA) can be applied to study online communities. After giving a brief summary about a code scheme that has been developed for investigating empathic online communities for older people, the methodology section gives a detailed description of procedures that were applied in order to investigate the social network patterns of the depression discussion board within SeniorNet. The results are reported and further interpreted in the discussion section. The conclusion summarises the findings and the contribution of this article and suggests further research directions in this area.

2. Literature review

This section starts with an overview of the basic concepts and constituents of a social network. Then, Social Network Analysis (SNA) is presented as a method to study relationships and interactions between people. Emphasis is placed on the applicability of SNA for studying online communities, and related studies that have applied SNA to study computer-mediated communication (CMC) are presented.

2.1. SNA and online communities

Social Network Analysis (SNA) is currently a highly discussed topic within the field of computer-mediated communication (CMC). A social network is comprised of actors and ties that link the actors. Actors can be people, nations, organisations etc. that are linked by ties, which indicate a relation between them. The links between different actors can be based on different characteristics, for example based on affiliation, or based on the exchange of resources. Garton, Haythornthwaite, and Wellman (1997) state that relations between nodes can be defined based on three characteristics: content, direction, and strength.

The information or resource that is exchanged between two nodes describes the content of the relation. In online communication, the content of a relation can differ, depending on what kind of information two related people exchange, e.g., information about work related issues, personal problems, emotional support etc. In a social network, a relation can have a direction but does not necessarily need to have one. For example, a directed relation exists when a resource is given from one person to another one (Garton et al., 1997). The strength of a relation can be defined by many different aspects. The frequency of contact (Granovetter, 1973), the importance of the exchanged information, and the amount of information that is exchanged are seen as indicators for the strength of the relation (Garton et al., 1997). Two nodes within a social network are connected by a tie. If the tie is maintained on basis of two or more relations, this tie is called multiplex. Multiplex ties are stronger in the sense that they are more intimate, supportive and last longer (Wellman & Wortley, 1990).

Social Network Analysis (SNA) is different from standard CMC methods, which often study computer-mediated relations separately from the network in which they occur. The strength of SNA lies in explaining social relations with the structure and patterns of the network in which these relations develop. The use of graphical representations of the network (sociograms) helps to identify people that are central or isolated in the social network, and spot asymmetries in the network structure (Scott, 2000). SNA therefore shifts the focus from individualism to structural analysis of the whole network (Garton et al., 1997). Until now the focus of CMC scholars was mainly on the investigation of human–computer interaction, person-to-person interaction via online technology, and the investigation of social interactions and computer-mediated communication in small groups. Therefore, the investigation of dynamics and communication of large online networks is a new and challenging field (Garton et al., 1997). Studies that investigated large online social networks are concerned with online social networks in the workplace (Wellman et al., 1996) and online communities (Wellman & Gulia, 1996).

In this study, we aim to use SNA to study an online support community for older people. Preece and Maloney-Krichmar (2005) define online community in terms of “people who come together for a particular purpose, and who are guided by policies [...], and supported by software.” Through communication and the exchange of information and other resources, people that meet in online communities form a social network. Wellman (1996) further states that in online communities, people exchange social support like in “real life”. Wellman and Gulia (1996) add that next to informational support, people also receive emotional support and companionship in online communities. Lewis (1994) adds that even long term and deep emotional relationships can develop in an online community. Online support groups, for example, are explicitly aimed at exchanging emotional support between people that go through a similar, challenging life situation (King, 1994). They place a special emphasis on the exchange of supportive and helpful information for their members.

2.2. Related studies

SNA has mainly been used to investigate offline social networks. Recent studies also focused on investigating the impact of online communication on offline networks. For example, Kavanaugh and Patterson (2001) investigated how social networks within a geographic offline community are influenced by the opportunity to reinforce existing relations and expand the social network through an online community. Surveys and interviews over a period of three years (1996–1999) were conducted with residents of the city of Blacksburg in Virginia in order to find out the influence and impact of the computer-mediated network on the social network of the ‘real’, offline life. Similarly, Hampton and Wellman (2000) also studied the influence of CMC on offline life. They compared the social network of wired residents with the social network of non-wired residents in a village in Canada.

Findings of these two studies show that computer-mediated networks help members of the community to reinforce their rela-
tions with other members of the geographic community and are even used to expand the current social network of some members. The opportunity to communicate online leads to an increased density and strength of already existing offline social networks. Thus, the internet can be used to reinforce and maintain local relations (Hampton & Wellman, 2000). Also, the engagement in the online community increased the involvement of the members in the offline community (Kavanaugh & Patterson, 2001).

In addition to investigating the relationship between online and offline social networks, SNA is also increasingly used to study online settings, for example in the area of e-learning (Laghos & Zaphiris, 2006). In order to investigate the differences between online and offline learning, Haythornthwaite (2000) compared the social networks of online distance learning classes with those of offline learning classes. Overall, she concluded that the online social networks were similar to their offline counterparts. The sizes of the ego-networks of the students were related to the size of the class, but the larger the size of the class, the lower the strength of the relationships. Furthermore, the members that communicated more frequently had interactions that were more social and emotional and formed a basis for strong relationships (Haythornthwaite, 2000).

Similarly to Haythornthwaite’s (2000) study, Aviv, Erlich, and Ravid (2003) also applied SNA in order to compare two different settings for learning. However, they focused solely on online settings, as they compared the network structures of a structured and a non-structured asynchronous e-learning board. They used SNA to investigate the development of cliques, the centrality of certain actors and the distribution of roles within the respective networks. They found that the members of the structured e-learning board developed a higher level of critical thinking and cognitive activities, formed more interconnected cliques and more of them took on leading roles compared to the social network of the unstructured e-learning board. Laghos and Zaphiris (2006) also found that the connectivity and inclusiveness of the network increased with time.

In addition to e-learning platforms, SNA is also increasingly used to study social interactions and communication patterns in other online communities. For example, Paccagnella (1998) applied a combination of content analysis and SNA in order to investigate the network structure and patterns of a computer conference called cyber_punk. He linked the language usage of members to their structural position in the social network. He concluded that the centrality of a member is positively correlated with an increased usage of terms that indicate a collective identity of the community and also an increased usage of computer network slang (Paccagnella, 1998). Concerning online communities for older people, we are currently only aware of one study that applied SNA in order to investigate online communities that are targeted at older people. Focusing on age differences, Zaphiris and Sarwar (2006) applied SNA in order to compare a teenage newsgroup and a newsgroup for older people. They investigated differences in the characteristics of messages and differences in the overall network structures between the two newsgroups. Whereas the teenage newsgroup had a higher number of visitors, messages per person, and on average longer messages, the newsgroup for older people had higher numbers of replies to messages and therefore showed a higher degree of interactivity, responsiveness and reciprocity. Overall, the newsgroup for older people was found to show more consistencies and stability in activity and behaviours of its participants (Zaphiris & Sarwar, 2006).

### 3. Methodology

In the presented study, SNA is used to study the social network structures that are formed in an empathic online community for older people. This study investigates the network structures of this online community and the link between the communication content and the network properties. Special emphasis was placed on investigating whether emotional and factual communication content is associated with different structures and patterns of the social network.

The basis of this study is a recent work we did where we studied the discussion board on the topic of “depression” within SeniorNet, an online community for older people (Pfeil & Zaphiris, 2007). The aim of this first study was to investigate empathic communication within that online discussion board. Four hundred (400) consecutive messages that were posted over a period of 1.5 years (posted from 6th August 2000 to 14th February 2002) of the discussion board about “depression” within SeniorNet were investigated and qualitative content analysis was applied. The number of messages was chosen to be large enough to do a meaningful analysis and the number of messages per day was fairly constant over the time of the sampling period. The design of the discussion board did not group messages into threads. Instead, the messages posted were displayed in chronological order. The messages were posted by 47 members of SeniorNet.

A code scheme that captured the communication of the discussion board was developed. It consists of 23 codes that were sorted into seven high-level categories. In our code scheme, consecutive sentences within one message that share the same meaning are taken as one text unit and coded into a single code. In total, the 400 messages consist of 869 text units.

In order to familiarize ourselves with the data and to get a first impression about the context of the depression discussion board, we first read all messages thoroughly. This helped us to view the data from an insider’s point of view during analysis and take its context into account. Also, reading about the background of SeniorNet, its purpose and the profiles of the members of the depression board, helped us to gather peripheral information about the members and the board. This aided us in the analysis.

In the second step, we analysed the first 400 messages of the depression board in chronological order, extracting key words and themes observed in the communication. When we had a collection of themes and patterns that described the data appropriately and completely, we sorted and grouped the notes and used them to develop the code scheme. This procedure was repeated iteratively, until a final code scheme was developed. Saturation was reached, when no new codes could be found and the data set could be sorted into the existing codes without any discrepancies.

To ensure objectivity in the coding procedure, we developed a detailed procedure as a guide for determining the unit of analysis. We further developed a detailed rule-sheet that guided the coder to code the text units independently based on their content. An inter-coder reliability test with a sample of the messages was carried with two independent coders. To measure the inter-coder reliability a sample of the messages was coded by two independent researchers. Cohen’s KAPPA was calculated to be 0.64. Once the inter-coder reliability concerning both, the segmentation and the codes was established, the full set of 400 messages was coded by one researcher. The rigorous approach that was taken to develop the code scheme and code the data ensured that the data was coded solely based upon the messages’ content. It also ensured that the code scheme was robust and thus serves as a valid basis on which to apply further quantitative analyses (e.g. SNA).

An overview of the characteristics of the categories is given in Table 1. Therein, the second column gives a short description of the characteristics of the respective category and the third column names the codes that are included in the respective category together with some examples that give a general idea about the characteristic of these codes.
Table 1
The developed scheme.

<table>
<thead>
<tr>
<th>Category</th>
<th>Description</th>
<th>Codes and examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Light support</td>
<td>The text unit is written in a generic way, for another person or the whole community.</td>
<td>- Best wishes (“Best wishes”, “Good luck”, “Happy Valentine’s Day”)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Light encouragement (“Hang in there”, “I am thinking about you”)</td>
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<tr>
<td></td>
<td></td>
<td>- Humour (“Who knows...it might have us ALL tap-dancing on the tables, lol”)</td>
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<tr>
<td></td>
<td></td>
<td>- Interest (“In which kind of senior housing do you live?”)</td>
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<tr>
<td>Community building</td>
<td>The text unit includes meta-information about communication activity on the discussion board.</td>
<td>- Different channel (“I will send you an email with the information”)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Own activity (“I am back again, I could not post the last week because...”)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Activity of others (“Good to hear from you, NAME. Yep, I have been worrying ‘bout you.”)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Togetherness (“Thank God for this board, as I can sit here and cry and rattle on—you are the only ones who understand.”)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Thanks (“Thanks for reading my post”, “Thanks for your advice”)</td>
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<tr>
<td>Technical issues</td>
<td>The text units are concerned with technical problems or suggestions to solve them.</td>
<td>- Technical problems (“Dear old aol is enough to depress anyone. Three times to write. ...”)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Technical suggestions (“Read in your browser screen and have Notepad or Wordpad minimised.”)</td>
</tr>
<tr>
<td>Deep support</td>
<td>Supporting text units are customised towards the unique situation of the target that the message is for.</td>
<td>- Reassurance (“Yes, air is so Good for you as is walking.”, “I think that it is quite normal for you to be depressed about loosing your leg.”)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Give help (“Listen, NAME—you need to level with your husband right now!”)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Deep emotional support (“Words are so hard right now. So I place my hand gently over yours and let love and sweetness flow through to you.”)</td>
</tr>
<tr>
<td>Self-disclosure</td>
<td>Text units in which people post information about themselves.</td>
<td>- Narration (“The current balance allows me the pleasure of short trips, art lessons, volunteer work, gardening, and writing songs”)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Medical situation (“Finally went to the doctor on this past Friday, and discovered I was suffering from a severe depression. I am now taking medication called Celexa, and it seems to help.”)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- General feeling (“I yawn all the time. I want to go to bed. I know you’re supposed to get out, but I don’t have the energy to do that much.”)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Ask for support (“NAME - I need you to help me find the answer to a problem in my family.”)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Similar situation (“I understand how you feel about your dad’s death. It took me years to come to terms with it, after my father died.”)</td>
</tr>
<tr>
<td>Medical facts</td>
<td>These text units include questions and answers about factual information within the topic (e.g., medication).</td>
<td>- Factual information (“In the case of bipolar manic-depression, surely that cannot be true, since it is a mood disorder caused by dysfunctional neurotransmitters in the brain.”)</td>
</tr>
<tr>
<td>Slightly off</td>
<td>Text units that are about others or about topics that strayed away from the theme of the discussion board.</td>
<td>- Factual question (“So in “both cases” situational depression and bipolar depression they alter chemicals in the brain?”)</td>
</tr>
</tbody>
</table>

The former study focused on the content of the discussions and compared the characteristics of the occurring conversation with attributes of offline empathic communication. You can read the full findings and more details about the characteristics of the codes in a recent paper that we published at (Pfeil & Zaphiris, 2007). One interesting finding of our analysis showed that the categories could be sorted into two groups, depending on whether their content was emotional or factual. In summary, the categories Self-disclosure, Community building, Deep support, and Light support were found to mainly contain emotional content whereas the categories Medical facts, Technical issues and Slightly off consist of mainly factual content. In addition, we found that messages within the category Self-disclosure are often posted as a means for asking for support. Rather than asking explicitly for help, members of the online community talked about their own situation in order to trigger supportive responses. Thus, we can conclude that messages in the category Self-disclosure are sent in order to ask for support and messages in the categories Light support and Deep support give support back to the person in need. Also, our finding show that there are distinct differences between the two supportive categories Light support and Deep support as light support was described to be more general and uplifting and deep support was described as being more serious and personalized towards the situation of the person in need.

The study reported in this paper focuses on the social network that emerges from the communication within the discussion group. To get an initial feel of the social network we first analyzed the network structure of all the investigated messages of the online community. Then, we went into more detail and investigated how dynamics of the network are related to the content. We focused specifically on the links between the content of the communication and the structure of the social network. Therefore, for each category (see Table 1), a sub-network that is based on the communication of the respective category was developed and studied separately. For example, all communication activities within the category Self-disclosure were modeled to form a social sub-network structure that is made up only of communication activities within this category. This category-specific sub-network of communications within Self-disclosure therefore represents relationships that is formed by communication activities within this category and can give an indication about the relation of this specific type of communication content to the network structure of the online community. This was done for all of the seven categories in order to find commonalities and differences between the structures of these seven category-specific sub-networks. The characteristics of the category-specific sub-networks are set into context to the content of the seven categories in order to find possible links between the content of the communication and the network structure it creates.

By focusing on the 400 messages that were posted over a period of 1.5 years, we feel that we covered a sufficient amount of messages and time of the life of the online community in order to claim
that our sample is representative of the whole online community. As a first step into investigating the association between content of an online community and its network structure, our study is based on a snapshot of data and investigates the association between content and social network structure in a period of a stable level of contribution and membership size. This is necessary to provide a basis for further studies that investigate whether and how this relationship changes over time in a longitudinal study. Compared to related work, both in the area of content analysis of online communities (e.g. Coulson, 2005; Preece & Ghozati, 1998) and social network analysis of communication activities (e.g. Paccagnella, 1998; Zaphiris & Sarwar, 2006), our sample size as well as the period of time that our study covers is similar and thus we consider them sufficient in order to allow for exploratory conclusions.

Understanding the links between communication content and the social network that is based on this communication can help us better understand communication dynamics and social network development in empathic online communities. In order to investigate the characteristics of the social network patterns of the discussion board about depression within SeniorNet, we first investigate the characteristics of the social network of the discussion board as a whole. Then, we study the sub-networks formed by communications within each of the seven categories separately. Focus lies hereby on the specific sub-network characteristics of emotional communication opposed to factual communication (see research question 1), on the differences between giving and seeking support (see research question 2), and between different kinds of support (see research question 3).

3.1. Data source

As mentioned above, our data set consisted of 400 messages that were posted between the 6th August 2000 and the 14th February 2002. In order to create a social network of the communication within these messages, the following procedure was established: All 400 messages were read in chronological order and for each text unit it was noted who sent it to whom. This was easy in cases where the author of the message wrote down whom the text units are meant for. Even if the author did not mention who the text units are for, this was in most cases easy to identify from the context of the message. In cases when the author targeted one text unit to two or more other specific members, each of the combinations (sender-target) was noted. For those text units that were not specifically targeted to anybody, the whole community was noted as the target and treated like a separate node. Additionally to the sender and receiver of the text unit, the category in which it was coded was recorded as well.

The result of this first step was a list of all text units, with its sender, receiver and the category it was coded into. For the social network of all 400 messages, irrespective of the categories, a matrix was created, in which all members (N = 47) of the discussion board where listed in the first column (sender) and first row (receiver) of the matrix. The number in the cells of the matrix indicated the number of text units that the particular sender sent to the particular receiver. An additional row and column was added and named “all”. This was done in order to account for the text units that were addressed to all community members and not to specific others. This matrix was used to establish the connections between participants within the online community and to create a sociogram of all investigated communications within the discussion board.

In order to investigate the category-specific sub-networks, a separate list was created for the communication within each category. These lists were then transformed into matrices. As a result of this procedure, seven matrices were constructed (one for each category) that included the number of text units that were sent from the senders to the receivers within the respective category. These matrices formed the basis of the SNA of the category-specific social sub-networks.

In the following section, the methods that were applied in order to address our study’s objectives are presented. We describe the measurements and calculations that were applied to analyse the social network of the discussion board and to study the differences and commonalities of the structures of the seven category-specific sub-networks.

3.2. Data analysis

For our analysis, the boundaries of the network were defined by the members that participated in the discussion board. This approach considers the occurrence of ties as well as the non-occurrence of ties between people that are active within the period of time of the data collection. As our data only captured the active members of the online community, we do not include passive members and members that might have been active before or after the time of our data collection in our sample. Instead, the network structure is solely based on the communication activities that took place in the 400 investigated discussion postings. This approach is similar to the application of SNA in other studies (e.g. Turner, Smith, Fisher, & Welser, 2005; Welser, Gleave, Fisher, & Smith, 2007; Zaphiris & Sarwar, 2006) that analysed network structures of CMC based on a sample of the online community(ies) under investigation. These studies looked at a sub-set of the online community members and the relationships they have with each other and based on the structure of this sub-network made assumptions and conclusions for the whole online community. We adopt this approach and focus on the associations between communication content and the relationships that are formed between people based on this content. We believe that our data sample is of sufficient size and captures a sufficient amount of time in order to indicate characteristics of the whole social network of all members and messages within the online community. In this paper we will refer to “social network” when talking about the relationships that are based on all 400 message exchanges. When talking about the networks based on category-specific communications, we refer to them as “sub-networks”.

For our study, we used the social network analysis software Cryam NetMiner II, version 2.5.0 to calculate the social network properties and visualize the respective sociograms. In the following, we describe the network-properties that we analysed in order to compare the seven category-specific sub-networks.

3.2.1. Number of text units sent to the whole community

It was investigated to what extent text units within a category-specific sub-network are addressed to the whole community instead of specific individuals. If the majority of text units within a category-specific sub-network are addressed to specific others, it is believed that this category includes personalised text units that take into account the situation, feelings and thought of the person that the text unit is meant for. On the other hand, category-specific sub-networks in which the majority of text units are sent to the whole community are believed to be inclusive for all members of the online community and encourage them to take part in the ongoing conversation.

3.2.2. Density

Density of the network is a commonly analysed network property within social network analysis. Network-density can be described as the ratio of existing ties within the network in contrast to the possible number of ties in the network (de Nooy, Mrvar, & Batagelj, 2005; Wasserman & Faust, 1994). Density in a directed network is defined as:
\[ A = \frac{L}{g(g-1)} \]

where \( A \) is the measure of density, \( L \) is the number of unvalued ties present in the graph and \( g \) is the number of nodes in the graph (Wasserman & Faust, 1994, p.129).

The more dense a network is, the more interconnected are the members of the network and the more do the members of the network have direct contact to each other (Garson et al., 1997). If all ties are present within a network (e.g. every person communicates with every other person) the density of the network is \( A = 1 \). If not ties are present, the density is \( A = 0 \). The denser a network is, the better are the members within this network connected to each other and the stronger is the connectivity of the whole network.

A dense category-specific sub-network would thereby indicate that the respective category is used in order to connect to others, whereas a more loosely-bound category-specific sub-network would indicate that this category does not lead to strong connections between the members.

The density of a directed social network can be further investigated by looking at the centrality degrees of the specific members (in- and out-degree). According to Wasserman and Faust (1994) the density is proportional to the average degree centrality of all nodes in the network. Thus, both density and average degree centrality can be used as a measure of the density of the complete network.

When investigating individual behaviour of people, it can be distinguished between in-degree and out-degree, in-degree measuring the number of incoming links and out-degree measuring the number of outgoing links for a node in the network.

The in-degree of any node is defined as:

\[ c_{in}(n_i) = \sum_j x_{ij} \]

where \( c_{in}(n_i) \) is the in-degree for node \( i \), and \( j \) ranges from 1 to the total number of nodes \( g \). \( x_{ij} = 1 \) when there is a tie from node \( j \) to node \( i \) and 0 otherwise.

The out-degree of any node is defined as:

\[ c_{out}(n_i) = \sum_j x_{ji} \]

where \( c_{out}(n_i) \) is the out-degree for node \( i \), and \( j \) ranges from 1 to the total number of nodes \( g \). \( x_{ji} = 1 \) when there is a tie to node \( j \) from node \( i \) and 0 otherwise.

Centrality degree for the whole network investigates the average of in- and out-degrees of all nodes in the network.

3.2.3. Inclusiveness

Inclusiveness measures the proportion of nodes that are connected with respect to all nodes of the network (Garson, 2008). This analysis focuses on the individual nodes of the network and investigates whether they are connected to the network or isolated. The inclusiveness of a network is defined as:

\[ I = \frac{\sum x_i}{g} \]

where \( I \) defines the inclusiveness of the network, \( g \) is the total number of nodes, and \( x_i = 1 \) when there is a tie coming from node \( i \) or going into node \( i \), and 0 otherwise.

People are included in the network by either sending a message to a specific other person, or by receiving a messages that was specifically addressed to them. A category-specific sub-network with a high inclusiveness indicates that communication within this category is general and many members are included in the communication within that category. On the other hand, category-specific sub-networks with a low inclusiveness indicate that only few and specific members communicate within that category.

3.2.4. Closeness (in- and out-closeness)

Closeness measures the average degree to which a person is close to all other people within the network either through a direct or through an indirect tie (de Nooy et al., 2005). Thus, closeness is defined as:

\[ CL = \frac{\sum x_i}{g} \]

where \( CL \) is the closeness of the network, \( g \) is the total number of nodes and \( x_i = 1 \) if node \( i \) is connected to another node and 0 otherwise.

Closeness gives an indication of the accessibility of the network to a person. If a person has a high closeness value, he has very good access to the others in the network (out-closeness), respectively in-closeness indicates whether the others can reach him easily (de Nooy et al., 2005).

3.2.5. Reciprocity

Reciprocity describes the ratio of the number of existing ties to the number of ties that are reciprocated. A tie is reciprocated if there is another tie between the two nodes pointing at the opposite direction. For example if node A and B are bi-directionally linked, there are two reciprocated ties between these nodes. Reciprocity is calculated as follows:

\[ R = \frac{\sum x_i}{L} \]

where \( R \) is the reciprocity of the network, \( L \) is the total number of ties within the network, and \( x_i = 1 \) if there is a tie from node \( i \) to node \( j \) and a tie from node \( j \) to node \( i \) and 0 otherwise.

Whereas the density investigates the ties independently of their direction, reciprocity emphasises the direction of the ties. In a network with a high reciprocity, people tend to respond to each other often and the relations between them are bilateral, whereas in a network with low reciprocity, more one-directional ties exist and the relations are more unbalanced.

3.2.6. Cliques

Cliques can be discovered with social network analysis, as the method investigates relationships between members of the social network and therefore also identifies sets of members that are highly interconnected. These sets are called cliques or clusters, and are characterised as a densely-knit and tightly-bounded set of members (Hanneman & Riddle, 2005). In a clique, each member is connected to each other member of the clique (Scott, 2000). In our analysis, a clique consists of at least three actors and each of the actors in a clique needs to be adjacent to all other members within that clique and no other member of the network is adjacent to all members of the clique. Note that not all of the ties within a clique need to be reciprocated (Wasserman & Faust, 1994). A category-specific sub-network with many cliques indicates that subgroups have formed that are highly dense. This could mean that communication within that specific category fosters strong friendships between certain people that form cliques.

4. Results

As mentioned above, in our code scheme, consecutive sentences within one message that share the same meaning are taken as one text unit and coded into a single code. Thus, one message consists of one or more text units. Our data set of 400 messages was separated into 869 text units. These text units were sorted into the se-
ven different categories. The frequencies of the categories are distributed as shown in Fig. 1. Additionally, the diagram gives the percentage of text units (TU) that were addressed to the whole community instead of specific others.

4.1. Network properties of the discussion board

Fig. 2 shows the sociogram of the investigated communication activities between individuals. Messages to the whole community have been discarded for this analysis. This explains the fact that the sociogram shows five isolated members. These members have only been posting text units to the whole online community instead of to specific others within the online community and they have not received any text units that were specifically addressed to them.

Overall, the network that is based on all investigated messages within the depression discussion board has a density score of 0.07. As can be seen from Fig. 2, many people are highly connected to the network (the nodes in the centre of the network), with a few people only connected through one connection, and five members not connected at all. Overall, the network shows an inclusiveness of 0.894 and a closeness of 0.186 (in-closeness) and 0.194 (out-closeness). The reciprocity score of the network is 0.539 which means that 53.9% of the ties are reciprocated.

4.2. Network properties for category-specific networks

4.2.1. Density

Table 2 shows the density and average in/out-degree centrality for the category-specific sub-networks for all categories.

Table 3 shows the average degree and density scores for the sub-networks of the emotional categories (the combination of the category-specific sub-networks of Self-disclosure, Community...
Due to the fact that data generated during social network analysis typically violates one of the key assumptions (independence of observations) of standard hypothesis testing techniques, a significant test using the permutation test technique was calculated (Borgatti, Everett, & Freeman, 2002). For the permutation test, the observed difference in means is compared to the difference found when members are randomly exchanged between categories. The results show interesting differences in the social sub-networks of the emotional and factual categories.

As the in- and out-degree of the individual members could be extracted, it was possible to investigate whether there were any significant degree centrality differences between the seven category-specific sub-networks and between the combination of networks of emotional and factual categories.

Due to the fact that data generated during social network analysis typically violates one of the key assumptions (independence of observations) of standard hypothesis testing techniques, a significant test using the permutation test technique was calculated (Borgatti, Everett, & Freeman, 2002). For the permutation test, the observed difference in means is compared to the difference found when members are randomly exchanged between categories. The results are significant if most of the randomly generated results show a difference in means that is smaller than the observed one.

The p-values for significant differences concerning the in-degree centrality and out-degree centrality are shown in Tables 4 and 5 (identified with the abbreviations “in” and “out”). p-Values that are below the significance level of 0.05 are marked bold (\( \cdot p < 0.05 \)).

### 4.2.2. Inclusiveness

Table 6 lists the inclusiveness scores for all category-specific sub-networks and Table 7 shows the inclusiveness scores for the sub-networks of the emotional and factual categories.

### 5. Discussion

In the discussion, we are going to provide the findings of some of the key comparisons across the seven category-specific sub-networks. Comparing the results and characteristics of the category-specific sub-networks and the comparisons between the sub-networks of the emotional and factual categories combined, we elaborate on the differences in structures between emotional and factual sub-networks (see research question 1). Investigating the characteristics of the empathic social networks in more details, findings show interesting differences in the social sub-networks of disclosing and supportive communication (see research question 2) and the social sub-networks of the two supporting category-specific sub-networks.

### Table 2

<table>
<thead>
<tr>
<th></th>
<th>Community building</th>
<th>Self-disclosure</th>
<th>Deep support</th>
<th>Light support</th>
<th>Slightly off</th>
<th>Medical facts</th>
<th>Technical issues</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Average degree centrality</strong></td>
<td>In: 0.037 (SD: 0.02)</td>
<td>In: 0.037 (SD: 0.02)</td>
<td>In: 0.037 (SD: 0.02)</td>
<td>In: 0.033 (SD: 0.01)</td>
<td>In: 0.014 (SD: 0.02)</td>
<td>In: 0.014 (SD: 0.02)</td>
<td>In: 0.003 (SD: 0.01)</td>
</tr>
<tr>
<td>Density</td>
<td>0.037</td>
<td>0.032</td>
<td>0.037</td>
<td>0.033</td>
<td>0.014</td>
<td>0.014</td>
<td>0.003</td>
</tr>
</tbody>
</table>

### Table 3

<table>
<thead>
<tr>
<th></th>
<th>Emotional categories</th>
<th>Factual categories</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Average degree centrality</strong></td>
<td>In: 0.067 (SD: 0.035)</td>
<td>In: 0.028 (SD: 0.034)</td>
</tr>
<tr>
<td>Density</td>
<td>0.067</td>
<td>0.028</td>
</tr>
</tbody>
</table>

### Table 4

<table>
<thead>
<tr>
<th></th>
<th>Self-disclosure</th>
<th>Deep support</th>
<th>Light support</th>
<th>Slightly off</th>
<th>Medical facts</th>
<th>Technical issues</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>p-Values</strong></td>
<td>In: 0.607</td>
<td>In: 0.904</td>
<td>In: 0.661</td>
<td>In: 0.002**</td>
<td>In: 0.001**</td>
<td>In: 0.000**</td>
</tr>
<tr>
<td></td>
<td>Out: 0.745</td>
<td>Out: 0.912</td>
<td>Out: 0.726</td>
<td>Out: 0.02**</td>
<td>Out: 0.023</td>
<td>Out: 0.000**</td>
</tr>
</tbody>
</table>

### Table 5

<table>
<thead>
<tr>
<th></th>
<th>Emotional categories</th>
<th>Factual categories</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>p-Values</strong></td>
<td>In: 0.001</td>
<td>Out: 0.016**</td>
</tr>
</tbody>
</table>

Table 9 shows the closeness scores for the sub-networks of emotional and factual categories.

A permutation test for significance revealed the following p-values concerning comparisons of closeness across the seven networks (see Table 10) and the comparison of the sub-networks of the emotional and factual categories (see Table 11). p-Values that are below the significance level of 0.05 are marked bold (\( \cdot p < 0.01 \); \( \cdot^* p < 0.05 \)).

### 4.2.3. Reciprocity

The degrees of reciprocity for the category-specific sub-networks can be seen in Table 12.

### 4.2.4. Cliques

The following Table 13 lists the number of cliques in the category-specific sub-networks.
Inclusiveness scores for sub-networks of emotional and factual categories.

<table>
<thead>
<tr>
<th></th>
<th>Emotional categories</th>
<th>Factual categories</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inclusiveness</td>
<td>0.872</td>
<td>0.617</td>
</tr>
</tbody>
</table>

5.1. Differences in the structure between emotional and factual sub-networks

As discussed above, the categories can be distinguished into two groups, emotional categories and factual categories. Hereby, emotional categories are characterised by a high level of emotional content and are of a more personal than factual nature. Please refer to Pfeil and Zaphiris (2007) for a more detailed description of the content and characteristics of the categories. Out of the seven categories, the following ones can be characterised as emotional: Self-disclosure, Light support, Deep support, and Community building. The remaining ones, Slightly off, Medical facts, and Technical issues are of a more factual nature compared to the emotional categories.

Concerning the density, it can be seen that the category-specific sub-networks of the emotional categories Community building, Self-disclosure, Deep support, and Light support have a higher density than the category-specific sub-networks of the factual categories Slightly off, Medical facts, and Technical issues (see Table 2). The most personal and very emotional and supportive category Deep support shows a high density (0.037). This shows that people who exchange support are personally connected to each other. Furthermore, the high density of the category-specific sub-network for the category Community building (0.037) shows that exchanging text units that aim to nurture the online community and build sense of togetherness among the members play a major role in connecting individual members to each other. This is not the case for the factual categories, where people seem not to specifically build relationships to others. Therefore the density of the factual sub-networks is lower. This tendency is also visible when comparing the sub-network of the emotional categories combined (the sub-network consisting of the addition of all emotional category-specific networks) compared to the factual categories combined (the sub-network consisting of the addition of all factual category-specific networks). As Table 3 shows the sub-network constructed of emotional categories shows a higher network density (0.067) compared to the density of the sub-network constructed of the factual categories (0.028).

As an example that illustrates the difference in the density between an emotional and a factual category-specific sub-network, Fig. 3 shows the category-specific sub-network of Deep support and Fig. 4 shows the category-specific sub-network of Medical facts. Comparing the two sub-networks we can see that the social sub-network of Deep support has much more connections between more members than the social sub-network of the category Medical facts.

All of these differences between the density of individual emotional and factual sub-networks are significant (see Table 4) as well as the differences between the addition of all emotional sub-networks and the addition of all factual sub-networks (see Table 5). The distinction in in- and out-degree between the emotional categories Community building, Self-disclosure, Deep support and Light support and the more factual categories Slightly off, Medical facts and Technical issues is clearly visible (see Tables 2 and 3). This finding indicates that emotional communication is linked to a dense network of the communicators, unlike factual communications which do not seem to be related to strong connection between individual members within the social network.

Furthermore, it was found that emotional communication is linked to a stronger inclusiveness compared to factual communication. The category-specific sub-network of the category Light support has the highest score in inclusiveness (0.702) (see Table 6). The sub-networks of the categories Community building and Deep support score also high in inclusiveness (0.681). Community building and support seem to be inclusive activities that a lot of people from the online community engage in, either as a sender or as a receiver (or both). On the other hand, the factual categories Medical facts (0.426), Slightly off (0.447) and Technical issues (0.106) have much lower scores in inclusiveness. Especially the rather low score of the category Medical facts is surprising, as we expected that talking about factual issues connected to depression is a major part of the topic of the conversation that everybody engages in, as everyone on the discussion board we studied has a connection to the medical side of depression. Also, we found a clear difference when comparing the inclusiveness of the sub-networks of the combination of all emotional networks (0.872) with the combination of all factual networks (0.617) (see Table 7). This finding stresses that it is the emotional communication activities that include the most members of the online community.

### Table 6
Inclusiveness scores for individual category-specific sub-networks.

<table>
<thead>
<tr>
<th></th>
<th>Community building</th>
<th>Self-disclosure</th>
<th>Deep support</th>
<th>Light support</th>
<th>Slightly off</th>
<th>Medical facts</th>
<th>Technical issues</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inclusiveness</td>
<td>0.681</td>
<td>0.66</td>
<td>0.681</td>
<td>0.702</td>
<td>0.447</td>
<td>0.426</td>
<td>0.106</td>
</tr>
</tbody>
</table>

### Table 7
Inclusiveness scores for sub-networks of emotional and factual categories.

<table>
<thead>
<tr>
<th></th>
<th>Emotional categories</th>
<th>Factual categories</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inclusiveness</td>
<td>0.872</td>
<td>0.617</td>
</tr>
</tbody>
</table>

### Table 8
Closeness scores for individual category-specific sub-networks.

<table>
<thead>
<tr>
<th></th>
<th>Community building</th>
<th>Self-disclosure</th>
<th>Deep support</th>
<th>Light support</th>
<th>Slightly off</th>
<th>Medical facts</th>
<th>Technical issues</th>
</tr>
</thead>
<tbody>
<tr>
<td>In-closeness</td>
<td>0.091</td>
<td>0.075</td>
<td>0.088</td>
<td>0.077</td>
<td>0.031</td>
<td>0.023</td>
<td>0.004</td>
</tr>
<tr>
<td>(SD: 0.075)</td>
<td>(SD: 0.073)</td>
<td>(SD: 0.09)</td>
<td>(SD: 0.071)</td>
<td>(SD: 0.04)</td>
<td>(SD: 0.034)</td>
<td>(SD: 0.012)</td>
<td></td>
</tr>
<tr>
<td>Out-closeness</td>
<td>0.092</td>
<td>0.076</td>
<td>0.088</td>
<td>0.079</td>
<td>0.03</td>
<td>0.023</td>
<td>0.004</td>
</tr>
<tr>
<td>(SD: 0.119)</td>
<td>(SD: 0.095)</td>
<td>(SD: 0.1)</td>
<td>(SD: 0.103)</td>
<td>(SD: 0.055)</td>
<td>(SD: 0.048)</td>
<td>(SD: 0.016)</td>
<td></td>
</tr>
</tbody>
</table>
In order to illustrate the differences between the inclusiveness of emotional and factual category-specific sub-networks, Fig. 5 shows the sub-network of the category Light support whereas Fig. 6 shows the sub-network of the category Slightly off. As can be clearly seen, the sub-network of the factual category Slightly off has many more isolated members than the sub-network of the emotional category Light support.

As Table 5 shows, there is also a big difference between emotional and factual category-specific sub-networks concerning the closeness of the network. Closeness measures the average degree to which people within the network are close to each other. The category-specific network of Community building (0.091/0.092 see Table 8) has the highest scores in in-closeness and out-closeness, and therefore provides a good opportunity for network members to relate and get close to each other. A high closeness indicates that it is easy for members to access resources of other members as the path from one member to other members is shorter. The high closeness within the category-specific sub-network of Community building shows that text units coded as Community building are being used by members within the online community to build a network of ties that provides easy and quick access for one member to other members of the online community. Apart from the category Community building, the other emotional sub-networks of Deep support (0.088/0.088), Light support (0.077/0.079) and Self-disclosure (0.075/0.076) also show a high closeness. When comparing the combined sub-networks of all emotional and factual categories (see Table 9), we can again see that the sub-networks constructed of the emotional categories have a much higher in/out closeness (0.179/0.067) compared to the sub-network of the factual categories (0.067/0.066). It can therefore be concluded that emotional communication is linked to a higher closeness within the network of the communicators. In contrast to that, factual communication is linked to a rather weak closeness within the network, as the scores of the category-specific sub-networks of Slightly off (0.031/0.03), Medical facts (0.023/0.023), and Technical issues (0.004/0.004) show. Concerning the in-closeness and out-closeness, all of the differences between emotional and factual sub-networks are significant (see Tables 10 and 11).

Summarizing the above findings, emotional communication content is linked to a dense social network, in which more members are included in the message-exchange, often as both, sender and as receiver of messages. Additionally, emotional communication is associated with closeness between the members of the online community. In contrast to that, the structures that were based on factual communication were found to be loose and only included a few of the members. Furthermore, the distances between members were much longer within the factual sub-networks. It can therefore be concluded that emotional message exchange is associated with a strong, close and connected network, which can be the basis for the development of friendships.

5.2. The characteristics of networks based on seeking and giving support

Investigating the characteristics of support-seeking and support-giving sub-networks, differences in the sub-networks of the categories Self-disclosure (posted in order to seek support) and the sub-networks of the both supportive categories (Deep support and Light support) could be found.

As Fig. 1 shows, there is a huge difference between the percentage of messages that is sent to the whole community between the category Self-disclosure and the supportive categories Light support and Deep support. The relative high percentage (56.04%) of codes

<table>
<thead>
<tr>
<th>Table 10</th>
<th>p-Values for closeness scores for individual category-specific sub-networks.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>p-Values</strong></td>
<td>Self-disclosure</td>
</tr>
<tr>
<td>Community building</td>
<td>In: 0.308</td>
</tr>
<tr>
<td></td>
<td>Out: 0.462</td>
</tr>
<tr>
<td>Self-disclosure</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>–</td>
</tr>
<tr>
<td>Deep support</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>–</td>
</tr>
<tr>
<td>Light support</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>–</td>
</tr>
<tr>
<td>Slightly off</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>–</td>
</tr>
<tr>
<td>Medical facts</td>
<td>–</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 11</th>
<th>p-Values for closeness scores for individual category-specific sub-networks.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>p-Values</strong></td>
<td>Factual categories</td>
</tr>
<tr>
<td>Emotional categories</td>
<td>In: 0.000**</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 12</th>
<th>Reciprocity scores for individual category-specific sub-networks.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Community building</td>
<td>Self-disclosure</td>
</tr>
<tr>
<td>Reciprocity</td>
<td>0.481</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 13</th>
<th>Number of cliques in the category-specific sub-networks.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Community building</td>
<td>Self-disclosure</td>
</tr>
<tr>
<td>Number of cliques</td>
<td>17</td>
</tr>
</tbody>
</table>
addressed to the whole community within the category-specific sub-network of the category *Self-disclosure* can be explained with the nature of the content of the text units within that category. The category *Self-disclosure* consists mainly of information that people give about themselves. This includes their medical history and situation, their feelings and things that happened to them in their daily life. Often, messages which include a high amount of self-disclosure introduce a new topic within the discussion group. *Self-disclosure* messages are also often written in order to ask for support. This explains why the majority of people address...
self-disclosing text units to the whole community instead of specific others. In contrast to that, the percentage of messages that are sent to the whole online community is much lower for the supportive category-specific sub-networks of Light support (28.75%) and even lower for Deep support (9.45%). As support is in most cases targeted to a specific other, the percentage of supportive text units that is sent to the whole community is much lower. This finding reflects the characteristics of the codes, as self-disclosing messages are aimed to reach as many people as possible in order to get a supportive response, and supportive messages are aimed to specific people the support is meant for. In order to illustrate the difference, Figs. 7–9 show the sociograms of the category-specific sub-networks for Self-disclosure (Fig. 7), Deep support (Fig. 8), and Light support (Fig. 9). The "all"-node (the node that represents the whole discussion board) is marked blue, and all other nodes that are connected to the all-nodes are marked orange. It is clear from these figures that the "all"-node has a much more important and central position within the category-specific sub-network of Self-disclosure than in the supportive category-specific network.

Focusing further on the two supportive networks, Figs. 8 and 9 also show the differences between the category-specific sub-networks of Light support and Deep support. When comparing these two sociograms, we can see that more nodes are connected to the "all" node in the category-specific sub-network of Light support compared to the category-specific sub-network of Deep support. This indicates that light support is slightly more often sent to the whole community members than deep support. This could be due to the fact that light support is more general in its nature and therefore can be addressed easier to all members of the online community. Deep support, on the contrast is tailored to a specific situation of another person and thus less likely to be sent to all members at once. The differences in the patterns between the category-specific sub-networks of Light support and Deep support reflect the different characteristics of the content of these two supportive categories. Although these categories are both emotional and supportive categories, some differences in the structure of the two category-specific sub-networks underline the differences of the characteristics of these categories. Similar to the interpretation of the sociograms with the "all"-nodes, an interesting finding is also the very low percentage (9.45%) of codes addressed to the whole community within the category-specific sub-network of the category Deep support. This again, reflects the nature of the content of text units within that category. Text units within the category Deep support are usually specifically tailored to the person that the support is meant for. Often, this means that this person is specifically addressed before the text unit starts. "[NAME], I really do feel for you. I've been in a similar situation. What I finally concluded is that I don't learn as quickly as I used to but what I learn is pretty much there to stay. It can be awkward, very awkward, but I have great respect and faith in your abilities." Compared to Deep support, the percentage of messages that is sent to the whole community within the category Light support (28.75%) is much higher. This reflects the rather general approach of the messages within Light support. Compared to Deep support, text units within Light support are more general and not as specifically tailored to the situation of a specific other than Deep support. For example, encouraging text units within the category Light support include "Hang on...", and "Best wishes..." which are commonly addressed to
the whole community. Therefore, it can be concluded that the degree to which text units within a category are sent to specific others instead of the whole community reflect the degree to which they have a personalised content.

Another difference in the structure between the category Light support and Deep support was concerning the reciprocity of the sub-networks. Although the topic of the two categories is support in both sub-networks and the only distinction is the type of the support, the category-specific sub-network of Light support scores much higher in reciprocity (0.366) than the category-specific network of Deep support (0.222) (see Table 12). The following Figs. 10 and 11 show this reciprocity (reciprocated connections are marked yellow). Although there are much more connections between the members within the category-specific sub-network for Deep support (81) than in the category-specific sub-network for Light support (71), only 18 ties are reciprocated in the Deep support sub-network, whereas 26 ties are reciprocated in the Light support sub-network.

This gives valuable information about the relation between the content of the two support categories and the structure of their sub-networks. The content within the category Deep support is shown to be one-directional. People send deep support to others, but do not get deep support back in response. On the opposite hand, exchanging messages and codes within the category Light support is associated with a highly reciprocated network structure. This might be due to the fact that content of the category Light...
support is often included as a kind of attachment in messages to others (e.g. I hope it goes well, I wish you all the best etc.). When getting a message which includes e.g. best wishes for the person, this person might answer to that message and include some encouragement or wishes as well. It might be the general nature of the content of the category Light support that offers the possibility to build a reciprocated network around that category. Unlike content in Deep support, which is highly personalised towards the recipient of the message, messages that contain Light support can be sent to anyone.

A large difference between the social sub-networks of the categories Light support and Deep support could also be found concerning the number of cliques that have been formed within these two social sub-networks. As Table 13 shows that the social sub-network of the category Deep support has a lot of cliques (23). This shows that the category-specific social sub-network of Deep support forms subgroups in order to exchange deep supportive messages. This can be seen as an indication for the fact that deep support is exchanged in small, personal and densely-knit subgroups. Deep support is limited to supporting specific single members of the community and the scope of the topic is limited to the situation or problem of this person. This is associated with the development of small cliques in the social network structure. The formation of cliques in the social sub-network of the category Light support is completely different than the one of the category Deep support. The social sub-network of the category Light support has fewer cliques (15). This indicates that light support is freely exchanged throughout the whole community without being specific to a certain subgroup. The content of the category Light support invites people to join in which is associated with the development of fewer cliques in the social network as everyone gets involved. The environment of a personal, small, and densely-knit subgroup that is necessary for deep support is therefore not existent for the exchange of light support. This fits into the characteristics of the two categories, as the category Deep support is more personalised and tailored to the situation to the receiver of the message than is the uplifting and more general content of the category Light support.

Summarising, it can be said that the difference between the characteristics of text units within the category Deep support and Light support has been shown to be also reflected in some of the properties of these two category-specific sub-networks. In our first study, deep support was defined to be personalised towards the situation of the person that the support is meant for. In contrast to that, light support was defined to be more general. Although light support is still support that can be addressed to a specific other, the content of this support is not specifically tailored to the situation of the members that the support is meant for. This is reflected in the properties of the sub-networks, as the work of the category Deep support has a lot of cliques (23). This shows that the category-specific social sub-network of Deep support forms subgroups in order to exchange deep supportive messages. This can be seen as an indication for the fact that deep support is exchanged in small, personal and densely-knit subgroups. Deep support is limited to supporting specific single members of the community and the scope of the topic is limited to the situation or problem of this person. This is associated with the development of small cliques in the social network structure. The formation of cliques in the social sub-network of the category Light support is completely different than the one of the category Deep support. The social sub-network of the category Light support has fewer cliques (15). This indicates that light support is freely exchanged throughout the whole community without being specific to a certain subgroup. The content of the category Light support invites people to join in which is associated with the development of fewer cliques in the social network as everyone gets involved. The environment of a personal, small, and densely-knit subgroup that is necessary for deep support is therefore not existent for the exchange of light support. This fits into the characteristics of the two categories, as the category Deep support is more personalised and tailored to the situation to the receiver of the message than is the uplifting and more general content of the category Light support.

Summarising, it can be said that the difference between the characteristics of text units within the category Deep support and Light support has been shown to be also reflected in some of the properties of these two category-specific sub-networks. In our first study, deep support was defined to be personalised towards the situation of the person that the support is meant for. In contrast to that, light support was defined to be more general. Although light support is still support that can be addressed to a specific other, the content of this support is not specifically tailored to the situation of the members that the support is meant for. This is reflected in the properties of the sub-networks, as the
category-specific sub-network of *Light support* has a higher percentage of text units that are sent to the whole community instead of specific others, shows a higher reciprocity and fewer sub-cliques than the category-specific sub-network of *Deep support*.

### 6. Conclusions

The aim of this study was to investigate the social network of an empathic online community. We chose to study the discussion board about depression within SeniorNet, an empathic online community specifically designed for older people. Separating the sub-networks dependent on the content of the communication, we also aimed to study the link between the characteristics of network structures and the content that the members of this empathic online community exchange.

We were interested whether the exchange of emotional communication content is associated with specific characteristics of the social network structure opposed to factual communication content (research question 1). Investigating the differences and commonalities of the category-specific sub-networks, it was clearly visible that emotional conversation is linked to a clearly different network pattern compared to factual conversation. People were more connected, closer to each other, and included more members in the sub-networks that were built on emotional communication compared to factual communication. This shows that emotional communication is an essential part of the discussion board that is associated with a strong connection between people.

Our second research question focused on the differences in the network structure between the two components of seeking and giving support. We found interesting differences between self-disclosing (seeking support) and supportive communication. Self-disclosing messages were often sent to the whole community. In contrast to that, supportive messages were rather directed to a specific member of the online community than to the whole community. As supportive messages were directed to specific others, they have a very important role in the development of relationships as they connect individual members of the online community. However, self-disclosing messages play also an important role for the development of a social network. The fact that self-disclosing messages are often sent to all members of the community shows that they are very inclusive and act as prompt to trigger responses from members of the whole community. This means that even members that are currently not very active are approached by self-disclosing messages which could encourage them to reply.

Differences could also be found between the category-specific sub-networks of *Light support* and *Deep support*, addressing our third research question (Are the different kinds of support that people exchange in online empathic communities associated with specific social network characteristics?). The sub-network that was developed from messages within the category *Light support* showed a lot of reciprocal links between members of the online community. This means that a lot of the relations that were developed through the exchange of light support were bi-directional and balanced. In contrast to that, the exchange of deep support is linked to a sub-network-structure that is imbalanced and distinguishes more between the role of the support-giver and the support-receiver. Additionally, the exchange of deep support seems to happen within cliques within the online community rather than within the online community as one group.
Our findings contribute to the area of CMC as they show how people form social networks in empathic online communities and how the content of the communications affects the structure and patterns of this social network. This knowledge can help practitioners and scholars to design successful empathic online communities and better understand how relationships between members within empathic online communities develop out of the conversations that they engage in.

6.1. Limitations

Our study was limited to the data of a discussion board about depression for older people. As the sample is rather small (400 messages written by 47 members over a period of 1.5 years), our results are exploratory and further research is necessary in order to validate the findings. For example, it is possible that the associations between the content of the communication and the social network structure change with the evolution of the online community (e.g. increase or decrease of message frequency). This needs to be investigated in future longitudinal studies that capture the whole empathic online community. Additionally, the topic of the discussion board might have influenced the findings. As “depression” is a very emotional topic, it is possible that the importance and prevalence of empathic messages in order to form relationships in this discussion board is due to the emotional character of the conversations. Furthermore, we developed the social network of the online community by looking only at the messages that have been exchanged. Additional interviews with the participants of the online community would have given further insights into the character and strength of the relationships between participants of the discussion board.

6.2. Suggestions for future research

Our findings show that there is a connection between the content of the communication within an online community and the underlying social network structure. Researchers are encouraged to further explore this connection by applying social network analysis to communications within online communities. Furthermore, more work is required to validate and generalise the findings of this study. Similar investigations of other online communities are necessary in order to better understand the connection between the content of the communication and the social network structure that emerges from it. Additional methods like interviews and questionnaires can be used to elicit further information about the relationships and characteristics of these relationships within a social network. Also, longitudinal studies that look at the relationship between communication content and network structure over time are necessary in order to investigate how these relationships depend on variables like the frequency of messages or a sudden drop or increase in the number of online community members. Other empathic online communities about other topics could be investigated in order to analyse the dependency of the social network characteristics on the topic of the conversation. Also, online communities for different user groups (e.g. older people vs. teenagers, empathic communities for people with special needs) could be compared in order to investigate the differences in the social network patterns of different user groups. More research into the characteristics of empathic online communities is necessary in order to understand its nature and value for the participants. If we understand how empathic online communities are formed and how they can be used to positively impact on people’s well-being, we can design online communities for specific user groups that match user’s needs and preferences.

References


