Structural Analysis of Communities of Practice: An Investigation of Job title, Location, and Management Intention

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Abstract. The community of practice phenomenon has been extensively studied in qualitative terms, but there has been relatively little research using quantitative techniques. This study uses the common social network measures of connectedness, density, graph theoretic distance, and core / periphery fit to examine how groups defined by different characteristics align with community of practice theory. Specifically, it investigates the roles of job title, location, and management intention relative to the structural characteristics of communities of practice. Workers were assigned to groups based upon their job title, job group, division, location, and emergent behavior (results of hierarchical clustering). Initial results suggest that grouping employees by their emergent behavior yields network measures that are most closely related to community of practice theory.

Introduction

Communities of Practice have received considerable attention from practitioners and researchers in the last ten years. From a strategic viewpoint, communities of practice are important to the firm because they are thought to be repositories for knowledge, its maintenance, reproduction, and extension (Brown & Duguid, 2001). While the specific terms and categories used by scholars to describe knowledge differ, they generally agree that there is something special about knowledge that enables firms to create value and achieve competitive advantage (Winter, 1987; Kogut and Zander, 1992; Teece, Rumelt, Dosi, and Winter, 1994; Davenport and Prusak, 1998).

The communities of practice phenomenon has been extensively described in qualitative terms, but there has been relatively little research using quantitative techniques, specifically social network analysis. Given the importance of communities of practice, it is important to better understand them and their structural properties. However, quantitative analysis presents challenging issues in part because of difficulties in defining communities of practice. The characteristics of what is considered a community of practice have subtly changed since the term was initially introduced (Lave and Wenger, 1991).

Specifically, the roles of location, functional discipline, and management intention are not clear. Early studies, such as those of copier technicians (Orr, 1996; Brown and Duguid, 1991) and claims processors (Wenger, 1998), depict communities of practice as emergent groups of co-located workers. Workers within communities of practice interact with each other to learn their jobs, address issues, and solve problems. More recent discussions of communities of practice (Wenger et al, 2002) relax these criteria. Distributed communities may now be the norm as new communication technologies enable global communication. Community members may be from different functional disciplines as complex tasks may require cross-functional inputs. Firms may try to create communities. Yet it is unclear if and under what conditions communities of practice can be created.

The goal of this paper is to draw upon common social network analytic measures to determine how the structural characteristics of subgroups of workers defined by job title, functional job group, company division, location, and level of mutual engagement relate to communities of practice theory. Social network measures of connectedness, density, geodesic distance, and core / periphery fit (Schenkel et al, 2001) will be used to assess the groups. This study uses behavioral data from email logs as quantitative measures of community member interaction.

Theory

The term “community of practice” is often casually used to mean everything from those working in the same workgroup to those with the same occupation to those with a common interest. Regardless of whether we are academics or practitioners, we have likely lived in a community at some point in our lives and felt as if we were members of that community. The term is familiar and may even conjure warm memories. The term practice is also relatively familiar and may bring to mind the idea of a medical practice, a law practice, or children practicing a sport or an instrument. Familiarity with the two terms contributes to the difficulty of a common definition. Those hearing the full expression for the first time will likely have some imprecise conception of the idea based on their experiences. Therefore, a discussion of some of the major works in the communities of practice literature is needed to help clarify the issues.

Communities of Practice

Lave and Wenger (1991) coined the term in their book about learning. Specifically they emphasized the social aspects of learning. They argued that learning was intimately tied to social practice and that learning through apprenticeships occurred via legitimate peripheral participation. Learners begin as peripheral participants (members) of a community of practice. Over time the learners acquire knowledge and skills, and they become recognized by other members of the community as possessing the appropriate knowledge for their community. They work with others to perform their duties and solve problems. As this occurs the learners become more experienced and may move toward being full participants in their community of practice. New members may come and go, or they may come and stay. Others may stay for a while and then move on. As this process occurs repeatedly the community of practice regenerates.

Brown and Duguid (1991), drawing upon Orr's (1996) ethnographic work about copy machine service technicians, link communities of practice to *organizational* learning and innovation. Like Lave and Wenger, Brown and Duguid emphasize the social aspects of learning and depict three aspects of a community of practice: narration, collaboration, and social construction. Narration through story telling helps workers convey problems they have encountered and solutions they have used to rectify the problems, but the stories also serve as knowledge repositories. The collaborative aspect of communities of practice is similar to Kogut and Zander's (1992) combinative capabilities. As workers individually reach the limits of their knowledge and experience, they may collaborate with others to exchange ideas and develop new shared knowledge. Social construction refers to the shared understanding that is developed and constructed by the community members. Members refine their practice and ensure new generations of members by engaging in and contributing to the practices of their communities. Learning, then, is a continuous process of drawing on previous experiences and conceptions of meaning, and incorporating new situations, impressions, and experiences. In doing so members consistently alter their previous understandings.

As appeal for communities of practice grew Wenger more fully developed the community of practice construct (1998). Community and practice are related through mutual engagement, joint enterprise, and a shared repertoire. Community members within and between communities negotiate meaning through the complementary processes of participation and reification. Participation is an inherently social activity. Employees work together and in the process build relationships. They develop routines, tools, and languages specific to their work activities. Through their interactions they develop joint interpretations and solutions to these work activities. Communities of practice are emergent and self-organizing. The complementary process of reification is the process of taking something abstract and representing it in something concrete. These concrete "things" are artifacts and include drawings, procedures, laws, tools, prototypes, spreadsheets, documents, etc.. They enable community members to focus on the artifact to create a greater group understanding. These objects and tools can change how work is performed. Today, many firms use their company intranets to store and disseminate documents.

More recently some of the characteristics of communities of practice seem to have been relaxed. Wenger et al (2002, pg 4) define communities of practice as "groups of people who share a concern, a set of problems, or a passion about a topic, and who deepen their knowledge and expertise in this area by interacting on an ongoing basis." This definition is sufficiently broad to include many different types and sizes of group interaction. Communities of practice can be small or big, co-located or distributed, homogeneous or heterogeneous, spontaneous or intentional, inside and across boundaries (ibid, pg 25). It would seem that these various types of communities would be substantively different from each other and from the original conception of communities of practice. The early exemplars of copier technicians and apprentices described emergent groups of co-located workers with similar jobs. Therefore, this paper seeks to use social network analysis to better understand how these various types of communities of practice differ. Specifically, it investigates the community of practice characteristics of location, functional discipline, and management intention.

Four social network analysis measures (Schenkel et al, 2001) of communities of practice - connectedness, density, core / periphery fit, and geodesic distance – will be used to analyze the different groups. These four network measures were chosen because of their implications relative to communities of practice. Connectedness is the first criteria checked for each group. Members of a community of practice participate with each other in pursuit of a common enterprise; mutual engagement is a key component. Regardless of their type of membership, members within a community are connected either directly or indirectly through other members to all other community of practice members; there should be no isolates.

The second measure calculates geodesic distance - or the shortest path between actors. The geodesic distance is calculated for each dyad and then averaged to determine the average distance among reachable dyads in the group. Learning is the foundation of communities of practice theory. All else being equal, knowledge travels faster when the distance between workers is less. It is therefore expected that communities will have relatively short average distances between dyads.

Density is the third measure calculated. For the valued email matrices, the density is the average cell value or the average number of emails sent. For the dichotomized email matrices, the density is the ratio of the number of actual connections between dyads divided by the number of possible connections. Community members are thought to exhibit strong ties. It is through repeated interactions that trusting relationships develop. It is therefore expected that the density for communities of practice will be relatively high.

Core / periphery fit is the fourth measure calculated (Borgatti and Everett, 1999). Communities of practice contain both core and periphery members. In an ideal core / periphery model core members interact with other core members and with peripheral members. Peripheral members are expected to interact with core members but not with other peripheral members. The fit is determined by comparing the actual interaction matrix with an ideal core / periphery matrix in which the cell values for the core block interactions are ones and the periphery block interactions are zeros. The actual matrix is permuted to position the rows and columns such that the core members and the periphery members are blocked. A correlation is then performed between the actual (permuted) data matrix and the ideal core/periphery matrix. Fit measures will vary between 0 and 1, with a perfect fit being a 1.

In summary, the literature on communities of practice has changed over the past decade such that the roles of location, functional discipline, and management intention are not clear. Community of practice theory suggests that, all else being equal, 1) there will be no isolates, 2) the average distance between workers will be relatively low, 3) community interaction density will be relatively high, and 4) core / periphery fit will be closer to 1. This paper seeks to understand how these structural characteristics differ in communities defined by management intention, location, and functional discipline.

Management Intention vs. Emergence

It is unclear if and under what conditions communities of practice can be created. Wenger (1998) argues that learning cannot be designed and organizations cannot create communities. They can only create the organizational and technical structures that may facilitate a community. The community emerges as members react to that structure and try to understand and make sense of their environment. Practice is not predetermined by the intended design; it instead emerges as members respond to it. Efforts to create communities may have unintended consequences. In trying to grow a community, the organization may inadvertently hurt it. Yet, many organizations understand the strategic importance of communities and are trying to create them (American Productivity & Quality Center, 2001).

> Proposition #1: The structural properties of communities of practice defined by emergence will be positively related to communities of practice theory predictions.

Location

Groups whose members are in relatively close proximity typified communities of practice. Co-location increases the chances of community members meeting face to face. It contributes to spontaneous meetings and encounters in which members can share ideas, problems, and solutions to problems. These repeated interactions allow members to determine what other members know, whom they can trust, and what is expected of them. Traditional face to face meetings provide the richest form of media (Daft and Lengel, 1984). They enable people to see subtle body language gestures that indicate boredom, attentiveness, concurrence, frustration, etc. Rich face to face meetings and interaction enable community members to read these signals. These "messages" are more difficult if not impossible to transmit with less rich media such as the telephone or email. Virtual connections also tend to "lose" people who are not actively participating in the meetings. It is not clear that communities of practice can occur through these virtual connections since the communities are said to emerge from repeated interactions of their members over time (Wenger, 1998; Brown and Duguid, 2000, Cohen and Prusak, 2001). The use of communication technologies may impede the existence of communities of practice.

However, electronic technologies are changing from information posting, database management, and document storage (considered more lean forms of communication) to the richer collaboration and group development that is more consistent with the theory of communities of practice. New communication technologies have brought with them an excitement for the potential connections they can provide across geographies. These technologies vary in their ability to provide connections. Media differ in their ability to process information because of differences in feedback speed, types of cues provided, and language use afforded by the media. Given the appropriate context, the phone, email, and the new advanced technologies may be part of what makes connection and engagement possible. These richer media enable people to communicate and work together across distance and time.

> Proposition #2: The structural properties of communities of practice defined by location will be positively related to communities of practice theory predictions.

Functional Discipline

By having practices in common, knowledge travels and is assimilated quickly (Brown and Duguid, 2000). However, it is not clear whether community members have the same type of job. The term practice is not clear. Much of the research on communities of practice refers to those with the same practice as those workers with the same occupation. Brown and Duguid (2001, pg 203) define practice as “undertaking or engaging fully in a task, job, or profession.” The inclusion of job and profession in this definition is consistent with the same job function interpretation of communities of practice, but the inclusion of task in the definition leaves open the notion that workers with different occupations may work together to complete a task.

This issue is consistent with the functional / cross-functional issues for technical organizations (Allen 1986, 1977; Van den Bulte and Moenaert, 1998). Managers need to organize to facilitate two types of communication – interdisciplinary and intradisciplinary. Functional expertise is necessary to perform in a quality manner and workers within the same discipline need to connect with each other to keep abreast of the latest technical developments. Functional expertise is communicated and combined by a common language within smaller communities of large complex organizations (Kogut and Zander, 1992). These organizations create knowledge (in part) by combining knowledge within and between groups. Thus, functional organization keeps workers connected to their knowledge base. Conversely, many complex tasks require multidisciplinary inputs. Workers from different professions or jobs must work together (i.e. engage with each other) to complete their tasks. Therefore, cross-functional organization may lead to more effective communication.

> Proposition #3: The structural properties of communities of practice defined by functional discipline will be positively related to communities of practice theory predictions.

This paper uses social network analysis to investigate the structural characteristics of different subgroups within a firm. It is an exploratory study that uses four commonly used network measures (connectedness, density, core / periphery fit, and geodesic distance) on subgroups to determine which subgroupings most closely align with the communities of practice theory. The workers’ job titles, job groups, divisional assignments, location, and hierarchical clustering of their dyadic interaction patterns define the subgroups.

Data

Data for this study are taken from email logs at the U.S. headquarters location of a global specialty chemicals firm. This firm has less than 1000 employees.

Communities of practice theory rests upon social interaction and mutual engagement by the workers. Email logs record employees participating with each other. The log data include the date, time, sender, and receiver(s) of each email. The data are transformed into square interaction matrices that are valued and directional. The email data are from the month of June 2002 and include the emailing behavior of 146 employees. This results in a sample size of 21170 interactions for the full group; the diagonals are ignored. Much of the analyses are performed on subgroups of these 146 employees.

Privacy concerns invariably arise when discussing email logs as a source of archival data. This issue was discussed with company personnel to better understand the company's privacy policy. Before receiving computer system user accounts and hardware, all U.S. employees at this firm are required to sign a form in which they acknowledge that 1) all data and messages are company property, 2) the employees have no rights or expectations of privacy, and 3) the company has the right to review, audit, and access all matters on the company's communication systems regardless of content or intended source. This policy implicitly allows for the use of logs to perform social network analysis. While analysis of email content would be allowed by this policy, the content of the emails was not used during the course of this study (nor was it in the logs or available to the researchers), which minimizes the impact on privacy. Additionally, this study only investigated the communications within the firm; no external email traffic was analyzed.

Not knowing the content of the emails is a double-edged sword. It protects privacy, but it may lead to suspicion of email interactions as an appropriate measure for community of practice interactions. Email can include jokes or important personnel decisions and each would count the same using the interaction as the unit of analysis – as one interaction. However, the communities of practice literature stresses the importance of water cooler talk and lunch time conversations in building trust; emailing jokes can be argued to be analogous to that water cooler talk. Additionally, previous research has shown that dyadic level emailing interaction is positively related to telephone interactions and proximity (Koku et al, 2000), where proximity was a measure for face to face interactions (Allatta, working).

The technology system logs are advantageous as a source of archival data for a number of reasons. First they do not suffer from low survey response rates; information for all workers in the system is collected. Second, the data are automatically collected and stored. They do not require the time and expense of having employees fill out surveys, nor the time and expense of the researcher to followup. And third, they provide an accurate record of worker behavior and are therefore not subject to the retrospective rationalization of the researcher or faulty memory of the worker being surveyed.

Individual and organizational attribute data were extracted from the company's human resources (HR) database. These data included demographic information such as job title, division, tenure at the company, gender, and birth date for each worker. Office maps were used to determine worker locations. There are two office buildings on this property. Office maps were available for only one of the buildings. Four major areas were identified for this building and workers were assigned to one of those areas based upon the section of the building in which their office was located. The forty-five workers located in the other building for which no map was available were assigned to one aggregated location.

Data for *subgroups* of workers were extracted from the overall sample of 146 employees based upon their job title, their job group, their divisional assignment, their work location, and the results of hierarchical clustering of the email matrix. The division category was included to serve as groups defined by management intention. The firm's top management team heads each division and employees report up through their divisions. There are seven divisions, but the vast majority of workers in our sample (140 of 146) are in five of these divisions. The location category is considered separately for theoretical reasons; however the firm's management team also determined worker office locations. Two months before these data were collected 101 of the 146 employees moved from one building to another due to renovations. (No office location map is available for worker offices before the move.) Interviews with employees indicate that many employees, who were co-located before the move, were also co-located after the move. However, management changed some employee groupings to facilitate better communication based on business processes. Correlation analysis between worker location and various employee attributes yields a significantly high correlation between location and job group. Job groups are job classifications such as 'information systems' or 'research and development'; they are not part of the management structure. Workers with different job titles may be in the same job group. For example, the R&D job group includes chemists, secretaries, technicians, etc. The hierarchical cluster grouping, based upon email interactions, was included to serve as emergent groups. The clustering is based upon behavioral data and reflects both the informal and formal communications between workers.

The original interaction matrix contained valued email sending and receiving data for the 146 employees for a one month time period. This matrix was then dichotomized three times using three different criteria. The first criterion was simple dichotomization of the data to make all cell values greater than zero (GT0) equal to one, else the cell values equaled zero. The second criterion was to make all cell values greater than one (GT1) equal to one, else the cell values equaled zero. This was done to remove the weakest ties. The third criterion was to make all cell values greater than four (GT4) equal to one, else the cell values equaled zero. This was done to obtain the stronger ties such that there was, on average, at least one interaction per week. Subgroup data (determined from job title, job group, division, location, and hierarchical cluster) were then extracted from each of these three dichotomized matrices. The four previously detailed social network measures were then calculated for each of the three dichotomized matrices for each subgroup. UCINET 6 (Borgatti, Everett, and Freeman, 2002) and NetDraw (Borgatti, 2002) were the software packages used to analyze the network data.

Results

Table 1 summarizes the basic statistics for the email interaction data for the overall group of 146 employees and the fifteen subgroups. The job title subgroups were chosen to maximize the number of workers. Of the 146 workers in the sample, 49 of them have unique job titles. Therefore the size of the groups defined by job title is relatively small. The minimum, maximum, average, standard deviation, and sum of the interactions is listed for each subgroup. The isolates show the number of workers who are not connected to any other member of the group. The number of groups indicates the number of separate subgroups within that category. For example, of the 12 chemists there are 2 chemists who are not connected to any other chemists; they are isolates. The remaining 10 chemists are split into 2 separate subgroups of chemists (see figure 1). The average graph theoretic distance is the average geodesic distance among those workers who can reach each other.

Results for the dichotomized data (greater than 0) are shown in Table 2. The number of workers in each subgroup is shown again for reference. Table 2 summarizes the results and provides the density, distance, and core / periphery fit *averages* for each subgroup category. Since there is no established database to determine acceptable values for communities of practice, the average values are evaluated (i.e. ranked) relative to the other values to determine which most closely align with communities of practice theory. The community type that is highest in density, lowest in distance, and closest to 1 for core/periphery fit is ranked first for that structural category. Figure 2 graphically represents the ranks of each group category for each structural measure. Table 2 and Figure 2 reveal that the hierarchical cluster category has the highest average density (0.605), lowest average distance (1.391), and second highest average core / periphery fit (0.518). Therefore, it ranks first for density and distance, and second for core / periphery fit. None of the three hierarchical cluster subgroups has isolates.

	#	Description	# Workers	Min	Max	Average	Std Dev	Sum	Isolates	Groups	Ave Graph Theoretic Distance
HQ		Headquarters	146	0	277	0.6645	3.4024	14068	1	1	1.911
Job Title	1	Chemist	12	0	2	0.0985	0.3451	13	2	2	1.682
	2	Customer Service	7	0	12	1.5714	2.1618	66	1	1	1.200
	3	Product Manager I	6	0	14	2.1000	2.9366	63	0	1	1.367
Job Group	1	R&D	44	0	27	0.6982	2.4098	1321	0	1	2.175
	2	Information Systems	12	0	54	3.2424	7.6020	428	0	1	1.402
	3	Marketing	7	0	42	4.7381	8.3753	199	0	1	1.738
Division	1	Sales & Marketing 2	34	0	32	1.3449	3.6895	1509	0	1	1.913
	2	Production, Mfg, Purchasing	22	0	277	2.9502	15.6569	1363	0	1	1.654
	3	Finance & Info Technology	31	0	54	1.9849	5.2267	1846	0	1	1.682
Location	1	Location 1	45	0	75	0.8995	3.0865	1781	0	1	1.964
	2	Location 4	28	0	42	1.6376	4.3563	1238	0	1	1.823
	3	Location 3	17	0	54	4.1544	8.5877	1130	0	1	1.391
Cluster	9	HCluster9	16	0	54	4.5500	9.1176	1092	0	1	1.436
	11	HCluster11	8	0	31	4.5893	7.2130	257	0	1	1.321
	12	HCluster12	19	0	41	3.4123	6.0294	1167	0	1	1.415

Table 1: Basic Statistics – Email Interaction Data

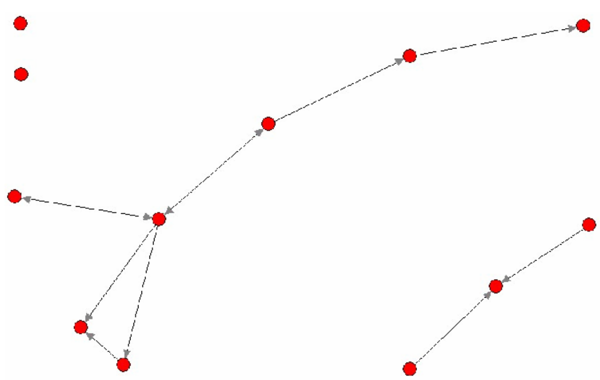
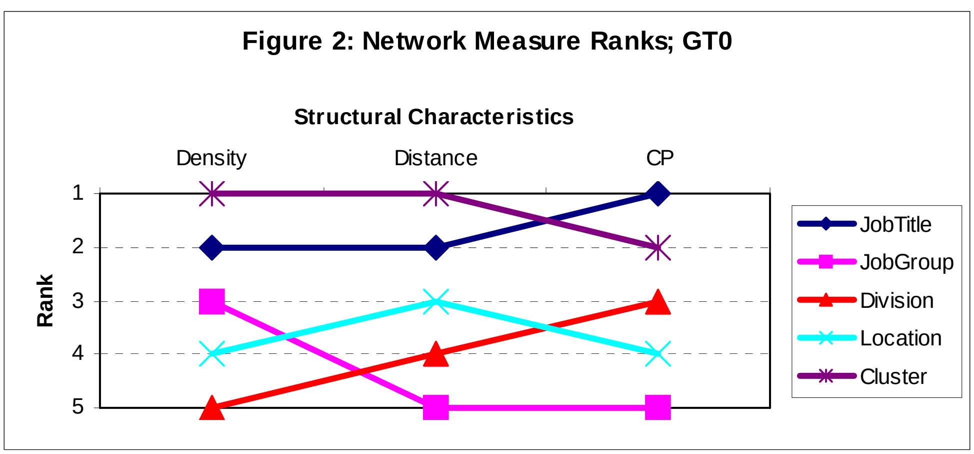


Figure 1: Job Title Group – Chemists: 2 Isolates, 2 Subgroups

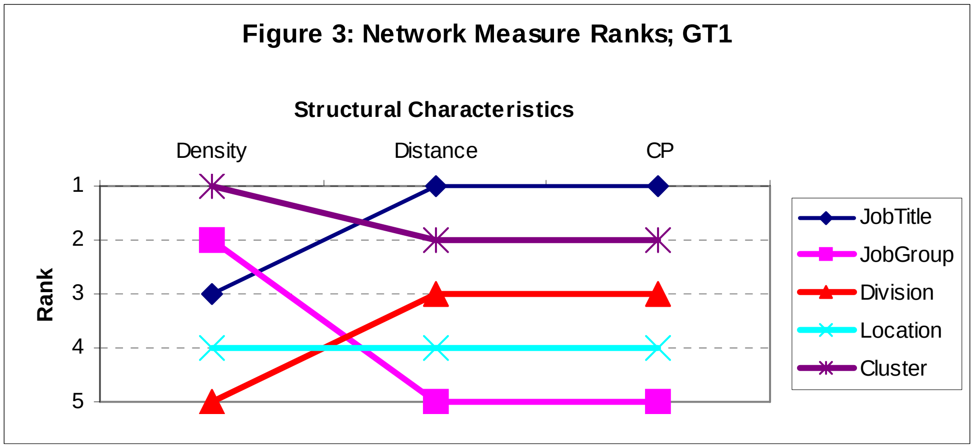
	#	Description	N Workers	Isolates	Groups	Average Density	Rank: Average Density	Average - Ave Graph Theoretic Distance	Rank: Average - Ave Graph Theoretic Distance	Average - Core / Periphery Structure	Rank: Average - Core / Periphery Structure
HQ		Headquarters	146	1	1						
Job Title	1	Chemist	12	2	2	0.440	2	1.416	2	**0.562**	**1**
	2	Customer Service	7	1	1						
	3	Product Manager I	6	0	1						
Job Group	1	R&D	44	0	1	0.432	3	1.772	5	0.325	5
	2	Information Systems	12	0	1						
	3	Marketing	7	0	1						
Division	1	Sales & Mktg 2	34	0	1	0.351	5	1.750	4	0.476	3
	2	Production, Mfg, Purch'g	22	0	1						
	3	Finance & IT	31	0	1						
Location	1	Location 1	45	0	1	0.382	4	1.726	3	0.467	4
	2	Location 4	28	0	1						
	3	Location 3	17	0	1						
Cluster	9	HCluster9	16	0	1	**0.605**	**1**	**1.391**	**1**	0.518	2
	11	HCluster11	8	0	1						
	12	HCluster12	19	0	1						

Table 2: Email – Dichotomized, greater than 0: Network measure averages and ranks



The job title category has the second highest average desity (0.440), second lowest distance (1.416), and highest average core / periphery fit (0.562). Two of the three job title subgroups have isolates, and one splits into two groups.

Tables similar to Table 2 were calculated for the dichotomized (greater than 1 and greater than 4) data. The resulting ranks are summarized in Figures 3 and 4. Figure 3 details the results of the dichotomized matrices that remove the weakest ties. The hierarchical cluster category ranks first in density, and second in distance and core / periphery fit. None of the 3 subgroups have isolates. The job title category ranks third in density, and first in distance and fit. Again, two of the job title subgroups have isolates and one has two separate groups.



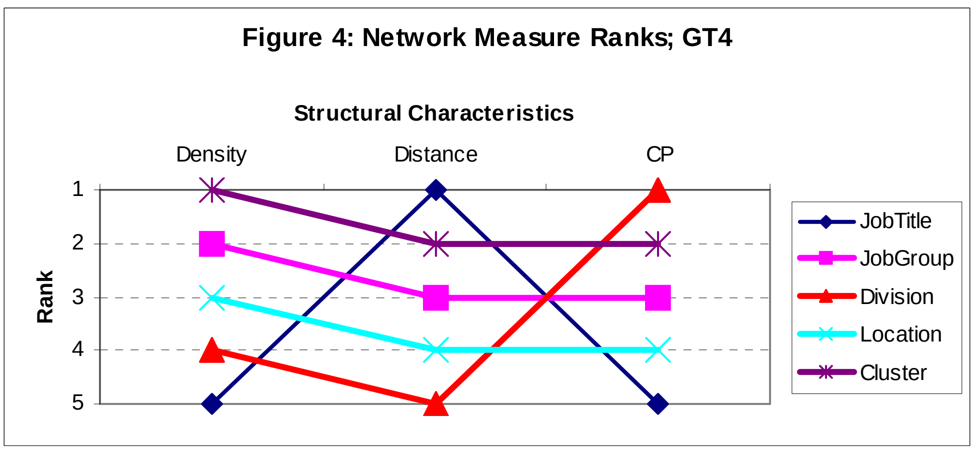


Figure 4 has the results of the dichotomized matrix with the stronger ties – those that are at least weekly interactions. The cluster category again ranks highest in density and second in distance and core / periphery fit. The job title category ranks first in distance, but last in density and core / periphery fit. All three job title subgroups have isolates with the chemist being totally disconnected. The job title, job group, division, and location categories all contain subgroups with isolates. The marketing job group and the sales and marketing division each have split into further subgroups.

The impact of group size (number of employees) on the network measures requires discussion. Inspection of the sizes of the hierarchically clustered and job title groups reveals that these categories of groups tend to have fewer employees than the other groups such that it might be size that accounts for the difference in network measures. This prompted further analysis of the data based on size. The data were grouped by size of the subgroups and averages of the network measures were again calculated.

	#	Description	N Workers	Isolates	Groups	Average Density	Rank: Average Density	Average - Ave Graph Theoretic Distance	Rank: Average - Ave Graph Theoretic Distance	Average - Core / Periphery Structure	Rank: Average - Core / Periphery Structure
Job Title	3	Product Manager I	6	0	1	**0.604**	**1**	**1.407**	**1**	0.465	2
Job Title	2	Customer Service	7	1	1						
Job Group	3	Marketing	7	0	1						
Cluster	11	HCluster11	8	0	1						
Job Title	1	Chemist	12	2	2	0.480	2	1.465	2	**0.501**	**1**
Job Group	2	Information Systems	12	0	1						
Cluster	9	HCluster9	16	0	1						
Location	3	Location 3	17	0	1						
Cluster	12	HCluster12	19	0	1						
Division	2	Production, Mfg, Purchasing	22	0	1	0.345	3	1.768	3	0.421	4
Location	2	Location 4	28	0	1						
Division	3	Finance & IT	31	0	1						
Division	1	Sales & Mktg 2	34	0	1						
Job Group	1	R&D	44	0	1	0.205	4	2.017	4	0.458	3
Location	1	Location 1	45	0	1						
HQ		Headquarters	146	1	1						

Table 5: Group Size Analysis: GT0 : Email – Dichotomized, greater than 0: Network measure averages and ranks

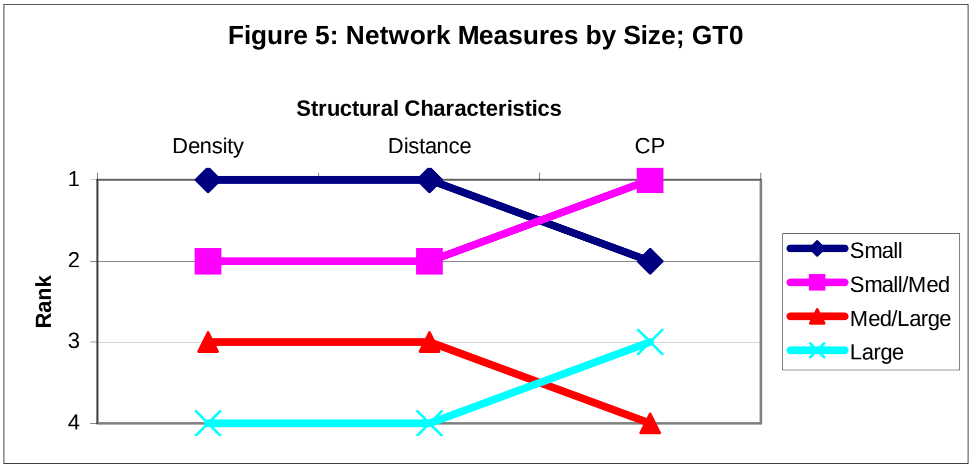


Figure 5: Network Measures by Size; GT0
Structural Characteristics
Density
Distance
CP
Rank
1
2
3
4
Small
Small/Med
Med/Large
Large

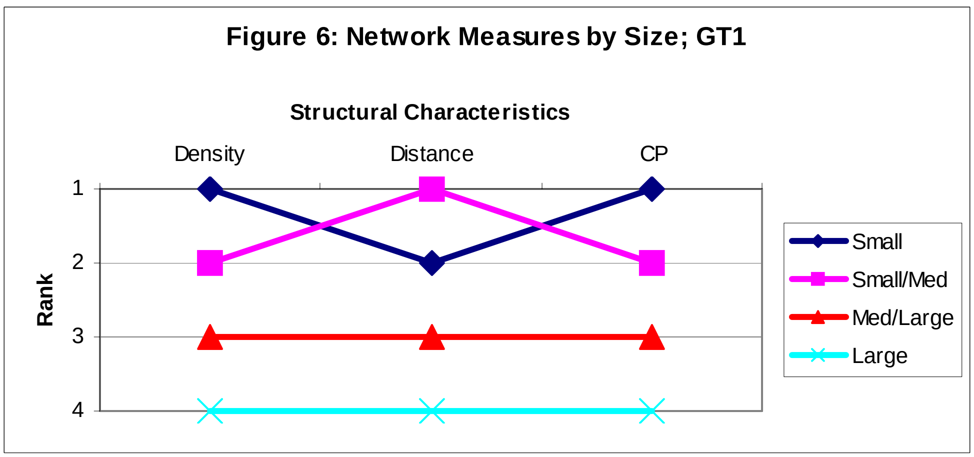


Figure 6: Network Measures by Size; GT1
Structural Characteristics
Density
Distance
CP
Rank
1
2
3
4
Small
Small/Med
Med/Large
Large

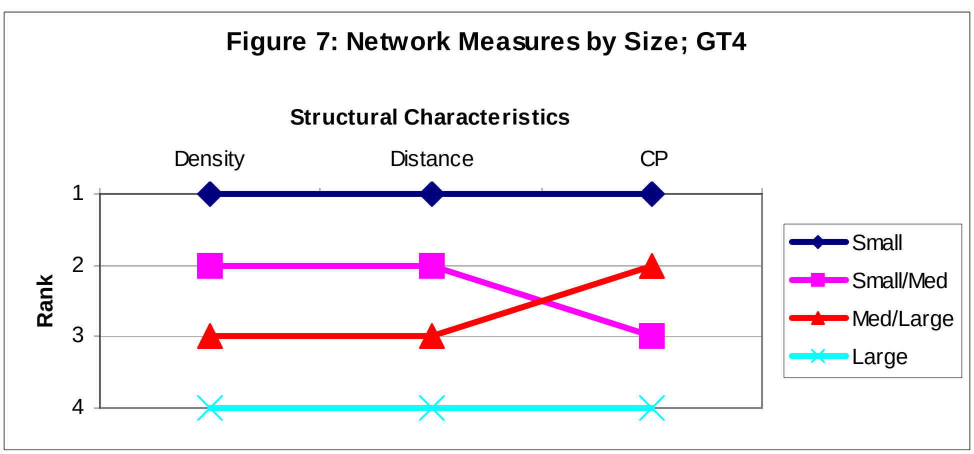


Figure 7: Network Measures by Size; GT4
Structural Characteristics
Density
Distance
CP
Rank
1
2
3
4
Small
Small/Med
Med/Large
Large

Table 5 details the results of the average values and their ranks of the network measures when the categories were determined based on size of the group. Table 5 and Figure 5 detail the results of the matrices dichotomized by values greater than 0. Figure 6 details the results with the weakest ties removed – data dichotomized by values greater than 1. Figure 7 shows the results with the stronger ties – data dichotomized by values greater than 4. All three figures reveal a consistent relationship between size and the network measures. The smaller groups are higher in density and core periphery fit, and lower in average geodesic distance.

Discussion

Knowing where knowledge in a firm is located is important because transferring and combining knowledge within and across groups can lead to value creation (Nohria and Ghoshal, 1997). Firms may benefit by applying their knowledge from one area into other related areas, from one group into other related groups, or from one business into other related businesses. Because knowledge is thought to reside in communities of practice, this study used social network analysis to analyze groups of workers with different characteristics to determine how their network measures related to community of practice theory.

The goal of this study was to better understand three characteristics of communities of practice: job title, location, and management intention. Four common network measures (connectedness, density, geodesic distance, and core / periphery fit) were calculated for various subgroups of workers defined by job title, job group, division, location, and hierarchical cluster. Theory would suggest that the density and core / periphery fit values should be high, while the average geodesic distance should be low for communities of practice. There should also be no isolates or subgroups. It was argued earlier that the roles of job title, location, and management intention are not clear in the communities of practice literature. These results support proposition 1 and suggest that emergent groups defined by actual interaction patterns (i.e. hierarchically clustered) match the communities of practice structural theory more closely than those defined by management intention. The structural characteristics of the clustered groups reflect communities of practice theory to a greater extent than do the groups defined by division and job group. The structural characteristics for job title are mixed. Many of the job title results ranked highest, but there were also more isolates and subgroups with this category. This requires further investigation.

Size of the group plays a part in the results of the structural analysis. Wenger et al (2002) allow for hundreds, even thousands of community members, especially for distributed communities. However, maintaining relationships takes time and energy and it is not possible to maintain repeated ties with large numbers of others. The nature of the relationships among members of a community will change as size increases. It is expected that larger communities will divide into subgroups by subject or location because there are costs associated with creating and maintaining ties as well as with transferring knowledge. It is reasonable then to expect that density will decrease and average geodesic distance will increase as group size increases. The core / periphery fit would also be expected to decrease as the larger groups split into smaller sub-groups.

Brown and Duguid's (2000) distinction between communities of practice and networks of practice proves useful here. Connections between members of a network of practice are looser than between those in a community; many people in a network may not even know or know of others in the network. For example, bus drivers in San Francisco do not belong to the same community as bus drivers in Buffalo, but they may belong to the same network of practice. It is through close ties and working directly with each other that people belong to the same community. A community involves people working, interacting, and interpreting together. Bus drivers from a specific area will be from the same community because they work together to cover routes, get around traffic jams, and deal with the public.

Disentangling size from the five categories of job title, job group, division, location, and cluster requires further investigation. For this data set there is relatively small variation of the group sizes within the categories and relatively large variation of the group sizes between the categories. Job title groups are only of small size. With the exception of the R&D job group, job groups are only of small size. Divisions are only of medium size; locations are of medium to large sizes; and hierarchical clusters are of small to medium sizes. Current analyses are being performed to further investigate the relationship between group size and the structural measures of the subgroups in this dataset. Future work will include vector analysis of website hit patterns to examine other types of communities of practice.

Conclusion and Future Work

Given the social nature of knowledge, the dispersion of many knowledge and information workers, and the impediments to learning, understanding how employees communicate within their communities of practice becomes important. In today's global environment, firms must be able to draw upon their knowledge resources in all locations in order to innovate and create knowledge, thereby creating value (Nohria and Ghoshal, 1997). They cannot remain competitive solely by appropriating the benefits of innovation from one location into other locations. This research seeks to contribute to the understanding of the characteristics of communities of practice and the nature of the work performed.

This paper argued that the roles of job title, location, and management intention were unclear in the current communities of practice literature. The study used the common social network measures of connectedness, density, graph theoretic distance, and core / periphery fit of various groups of communities of practice as defined by job title, location, and management intention and determined how these measure aligned with community of practice theory. Initial results from this work suggest that grouping employees by their informal communications (hierarchical clustering of their interactions) yields network measures that are most closely related to community of practice theory. The network measures for management-defined groups (division) rank lower. This is consistent with the theory that communities of practice are emergent structures, not structures defined by management. The network measures for job title are mixed. The job title network measures rank relatively high compared with the other methods of grouping, but these groups also tended to have more isolates and subgroups. The network measures for location rank in the middle to lower range.

Group size seems to be confounded with group categories in this data set. Work is currently being performed to further analyze this relationship with this data. Future work will investigate other types of communities of practice using vector analysis of company intranet hits.

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