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Social Networks and Performance in Distributed Learning Communities

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ABSTRACT

Social networks play an essential role in learning environments as a key channel for knowledge sharing and students' support. In distributed learning communities, knowledge sharing does not occur as spontaneously as when a working group shares the same physical space; knowledge sharing depends even more on student informal connections. In this study we analyse two distributed learning communities' social networks in order to understand how characteristics of the social structure can enhance students' success and performance. We used a monitoring system for social network data gathering. Results from correlation analyses showed that students' social network characteristics are related to their performance.

Keywords

Social networks, Social capital, Knowledge sharing, Distributed learning communities

Introduction

Social capital refers to the stock of social trust, norms and networks that people can draw upon to solve common problems; it implies connections among individuals as well as the value accrued from these connections (Daniel et al., 2002). Usually when we think of what people use when seeking information about a particular subject, we think of databases, the Web, portals, intranets or more traditional sources such as books, encyclopedias, manuals or records. However, a significant component of information used by each person comes from his or her network of interpersonal relationships (Cross et al., 2001). Processes of production and use of knowledge are significantly influenced by the way knowledge is shared and disseminated through social networks. These sets of interpersonal relationships characterize the way a community or a working group develops its own activity. Social Network Analysis (SNA) techniques provide a rich and systematic means for assessing informal networks by mapping and analysing relationships among people (Cross et al., 2001) and can be a valuable analytical tool for examining complex social processes. Thus, SNA techniques raise the possibility of intervening at critical points within an informal network (Cho et al., 2007). Understanding the structure and dynamics of a community's social network is essential in supporting the implementation of knowledge management strategies. An efficient management is the result of a process that requires understanding which parts have the capacity to create and extract, so that this value can be multiplied by the interaction and cross-fertilization of skills, fostering the flow and exchange of expertise (Edvisson & Malone, 1999). There is abundant cross-sectional evidence of performance correlated with network structure (Burt & Ronchi, 2007). Efforts to strengthen connections or to reinvent organization structure in order to increase the likelihood of strategic success should be based on network information. By revealing organizational trends and identifying the most influential individuals, the network information prevents duplication of efforts and facilitates the distribution of investment among various stakeholders (Clark, 2006; Hoppe & Reinelt, 2009).

Social networks also play an essential role in learning environments as a key channel for knowledge sharing and as a source of social support. Learning activities involving group work and collaboration promote learner-to-learner interactions in order to support the co-construction of knowledge and the sharing of information and resources (Dawson, 2008). Traditional instructional design will continue to be important, but additional emphasis on diverse multifaceted networks needs to be placed to address both the way knowledge exists in networks and the way learning develops and forms (Siemens, 2008). From a social perspective, learning is a social and collective outcome achieved through seamless conversations, shared practices, and networks of social connections (Cho et al., 2007). While learners are doing a learning task or activity, they usually look for some knowledge through their informal networks of colleagues and friends. For most people it is much easier to ask for help from a friend or close colleague than an expert in the area who is totally unknown (Braun et al., 2007). Usually they choose not to go to the channel of the highest quality of information, but rather to go to the channel of the highest accessibility (El-Bishouty et al., 2010). It is therefore expectable that social network structure may explain what makes some individuals or groups more creative and effective in their use of knowledge than others, and hence that social network position and structure are related to students' success and performance.

The aim of this work is to investigate the relations between social networks and students' performance in two distributed learning communities. When a learning community is geographically distributed, opportunities for the learner to engage with peers in a collaborative environment are problematic given the lack of spatial and temporal requirements associated with traditional classroom settings (Dawson, 2008). In these contexts, it is even more pertinent the concern for a social structure that supports an environment of sharing and collaboration, since knowledge sharing does not occur so spontaneously as when a working group shares the same physical space (Gutwin et al., 2007; Zheng & Yano, 2007). In order to better understand social capital and how social network could be related to the outcomes, we analysed the role that social network structure can have on students' performance. Descriptive information on the communities' social network is presented and the correlations between students' social network characteristics and students' performance are analysed.

Social Network Structure and Performance

Knowledge is created and exchanged to a large extent through informal social interactions (Cross, et al., 2002; Storberg-Walker & Gubbins, 2007; El-Bishouty et al., 2010). In addition, the knowledge flows depend on the connections between individuals and on their attitude about sharing knowledge (Inkpen & Tsang, 2005; Ipe, 2003). Informal networks are based on spontaneous contacts, by self-initiative and self-motivation and evolve according to mutual trust, reciprocity and friendship grow (Wang & Yang, 2007; Lin, 2007). The physical proximity, frequent contact, similarity of languages, knowledge and experiences as well as beliefs and attitudes, facilitate knowledge sharing (Novak & Wurst, 2005). Informal networks also play a key role in facilitating coordination and avoiding potential conflicts (Garcia-Perez & Mitra, 2007).

Social network analysis is frequently applied in a knowledge management perspective with the purpose of helping organizations to better take advantage of the knowledge and capabilities distributed across its members (Borgatti et al., 2009). Burt (2009) highlights two facts that were revealed by SNA empirical research: 1) people tend to cluster, forming groups according to their respective institutions, projects in which they are involved, sharing of physical spaces or common interests, 2) the interaction is much more common within a group than inter groups, so people in the same group tend to have the same ideas and opinions, to interpret the past in the same way and to have similar expectations for the future.

Although there is interest in network antecedents, the primary focus of network research has been on the consequences of networks (Borgatti et a., 2009). It is believed that individuals with fewer constraints and more opportunities are those that are in favorable positions in the social network (Hanneman & Riddle, 2005). Network position might also provide an ability to help absorb knowledge acquired elsewhere (Cross & Cummings, 2004). Sparrowe et al. (2001) showed that individual job performance was positively related to centrality in advice networks and negatively related to centrality in hindrance networks composed of relationships tending to thwart task behaviours. In a study involving managers and highly skilled professionals, Song et al. (2007) found associations between centrality with creative and efficient use of knowledge. At a group level, researchers tended to emphasize variation in social structure across different groups, using these variations to explain differences in outcomes (Borgatti et al., (2009). Cohesive and closed networks might promote a trust and well-known environment that enables knowledge sharing. However, closed networks might also have unintended consequences in performance if they result in comfortable interactions but do not allow gathering the most relevant knowledge for the task at hand (Cross & Cummings, 2004). Reagans and Zuckerman (2001) found out that R&D teams with higher productivity were those with higher heterogeneity and higher social network density. Creativity and innovation are facilitated by an easy access to diverse and non-redundant information and the heterogeneity of network is positively associated with strategic and creative results. Moreover, these authors have shown that social cohesion, measured by the density of relationships, affect the willingness and motivation to share knowledge, and hence productivity. Sandstrom and Carlsson (2008) showed that closure and team heterogeneity were related to performance measured in terms of efficiency and innovativeness. Hansen (2002), working with different units and project teams of a large multinational, confirmed the correlation between highly connected teams and their efficiency in knowledge sharing.

Centrality metrics measure the extent to which a given individual is connected to others in a network. Degree centrality refers to the extent to which an individual has numerous connections to other members, reflecting his or her level of social activity. Individuals who exhibit high values of degree tend to occupy prominent positions characterized by intensive interactions and knowledge sharing activities (Song et al., 2007). Because of their numerous connections to others, central individuals have more relationships to draw upon in obtaining resources and so are less dependent on a limited number of individuals (Hanneman & Riddle, 2005). Individuals with fewer contacts mostly occupy peripheral positions with little access to communication and information (Song et al., 2007). Degree centrality is related to reciprocal links (Ahuja & Carley, 1999), access to tacit knowledge (Hansen, 2002), and had been positively associated with performance (Sparrow et al. 2001; Hansen, 2002; Song et al., 2007; Cho et al., 2007). Given these arguments we decided to explore the association between degree centrality and student's performance, and hypothesis H1 was tested:

H1. The greater the number of a student's contacts, the greater the student's performance.

Closeness centrality reflects the individual's distance to all others on the network. While degree centrality measures only the direct contacts of an individual reflecting what is happening locally, closeness translates the individual's position compared to the entire community (Hanneman & Riddle, 2005). Closeness centrality is associated with proximity and close relations that foster a trusting environment, which facilitates the sharing of resources and tacit knowledge (Hansen, 2002). People that have direct links or shorter distances to all others become aware of opportunities earlier than those with longer paths (Song et al., 2007). The probability of information distortion and unawareness about what is happening is high when indirect relations are involved. Closeness centrality has been associated with efficient knowledge sharing and better performance (Ahuja & Carley, 1999, Song et al. 2007; Sandstrom & Carlsson, 2008). In this study, we tested the possible association between closeness and performance:

H2. The smaller the distance of a student to all others, the greater the student's performance.

Betweenness centrality captures the property of frequently lying along the shortest path between pairs of persons. Higher values of betweenness are associated with opportunities and power in the sense that one individual can control and change the communication flow passing through in order to better serve their own interests (Hansen, 2002; Borgatti et al. 2009). People occupying these positions constitute access bridges for those who are not directly connected and also benefit from access to a wider and more diverse source of resources, knowledge and experience (Tsai & Ghoshal, 1998; Cho et al., 2007). Higher values of betweenness are also associated with the ability to obtain and apply relevant information to solve problems effectively and efficiently (Cross & Cummings, 2004). Several studies associated empirically betweenness with performance (Tsai & Ghoshal, 1998; Cross & Cummings, 2004; Burt, 1997 and 2005, Song et al., 2007) which yields in the following hypothesis:

H3: The higher the student's level of interconnection among others, the better the student's performance.

Method

Participants

We conducted our research with two different distributed communities: 1) the Multimedia Engineering PhD Programme of Polytechnic University of Catalonia, Spain (UPC); and 2) the Basic Education Distance Learning Course of Polytechnic Institute of Leiria, Portugal (EB).

The UPC community is a multidisciplinary group of sixty two researchers, including fifty two PhD students. In this community, multimedia engineering projects and services rely upon multidisciplinary teams that bring together different expert knowledge domains (engineers, designers, teachers, mathematicians, anthropologists, psychologists). There is a central unit of 21 people located in Barcelona, Spain, but the rest of members are geographically distributed through several countries (Venezuela, Mexico, Colombia, Portugal, Denmark, and USA) and primarily maintain virtual interaction with others. This community uses a web platform for information sharing and there are weekly seminars (virtual conferences) for individual and group research presentations. Most communications occur outside this platform through e-mail, chat, or, in some cases, face-to-face encounters.

The EB community includes nineteen students and five teachers and uses a learning managing system (LMS) for daily course activities. This is also a geographically distributed community with most student-teacher interactions occurring in the LMS. Student-student interactions occurred mainly through e-mail and chat. All the community has face-to-face meetings at least once a month for work presentations and individual evaluations.

Data Collection

Social network data. To collect data we used a social network monitoring system – KIWI (Knowledge Interactions to Work and Innovate). KIWI is a web-based application with two separate views: one for data collection and other for feedback. The system provides users with a gathering tool for registering their interactions and automatically analyses and presents social network information through a visualization tool. Explicit social network information is extracted from a database through social network analysis (SNA) techniques. This system was developed mainly to be applied in distributed communities (for more information, see Cadima et al. 2010) and depends on active participation of users in the data gathering process. In addition to its potential to go further in a systematic analysis of social network by researchers and community managers, the system supports social network awareness of users by making the hidden networks visible to all community, without abstracting or evaluating users' behaviours. By directly asking users about their interactions it is possible to monitor every kind of interaction, from face-to-face meetings to mail and chat interaction, without implying major changes to users' current behaviour (the imposition of new communication tools could change the existing spontaneous informal network and would not ensure that all of what was happening was being recorded). Although the required involvement in the data gathering process creates additional workload for users, potentially leading to a disparity between effort and benefit (Van Baren et al., 2004; Rittenbruch et al., 2007), we note two advantages of this strategy. First, this option can act as a filtering strategy which will increase the extraction of meaningful information and decrease the burden in analysis, instead of producing extensive data as most monitoring systems do, which in turn would require considerable effort to uncover significant relationships within the group (Chen et al., 2003). Second, this strategy is likely to promote individual responsibility, to strengthen trust among participants, and to improve self-awareness, self-direction and self-management of their own activities (Zheng et al., 2007).

In attending to map social network structure, the system was integrated into communities' web platforms and a field test was conducted in each community. Participants were asked to respond to KIWI data gathering tool every week, identifying those people with whom they interacted for advice and knowledge sharing during that week. Participants were explained that every meaningful interaction should be point out, including formal or informal communications and face-to-face or distance communications. A weekly e-mail was send remaindering participants (including students, teachers and directors) to access KIWI and their accesses were monitored. In UPC community, the system was used during an 18 weeks period and in EB community it was used for an 8 weeks period. From the social networks data generated, we computed degree, closeness, and betweenness centrality scores for each individual using Ucinet (Borgatti et al., 2002) and NetDraw (Borgatti, 2002). In both communities, social networks that were considered include everyone in the community and therefore the computed measures for students take into account the links students-students and students-teachers or students-directors.

Performance data. In evaluating students' performance we used separate instruments for UPC and EB communities given the distinct objectives and working methods of each community. In UPC community, individual performance was assessed by directors using seven items tool developed by Sparrowe, Liden and Kraimer (2001) on a scale ranging from "very poor" (1) to "very rich" (5). Items addressed the quality and quantity of work and the initiative, cooperation, timeliness, and overall performance. A total of forty six students were assessed, with internal consistency of α =.96. In the EB community, individual performance metrics were obtained from students' grades at the four curriculum units they attended during the eight weeks of the field test. The social network monitoring system has been used from the first week of activities until the last week of final evaluations. According to Chen et al. (2003) these ratings are a good indicator of individual performance in computer supported collaborative learning (CSCL) contexts. An average grade was computed for fifteen students, with internal consistency of α =.72.

In both communities, correlation analyses between network characteristics and performance were applied to a students' group.

Results

Social Networks

During the field test, participants were asked to register their both formal and informal interactions in order to map social network structure. The individual mean average in UPC community was 6.8 interactions by person by week (SD = 4.4). Figure 1 displays the connections registered by the sixty two members of UPC community during the eighteen week field study, and include directors (triangles), advanced students (squares) and beginning students (circles). Colours are used to identify distribution among countries: people from Spain are in red, from Portugal in black, from Venezuela in blue, from Mexico in grey and people from other places (USA, Denmark, and Colombia) are in pink.

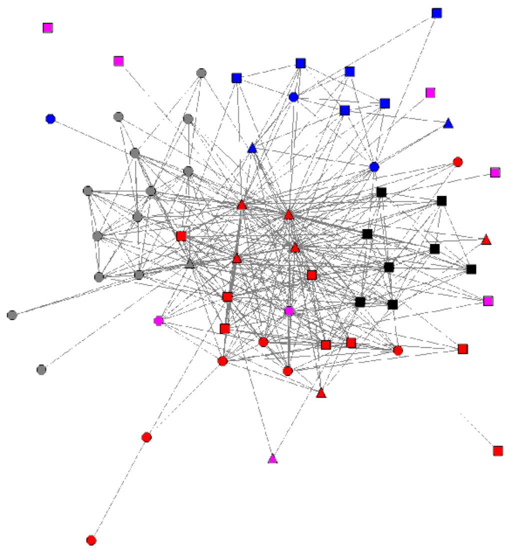

Figure 1. UPC social network (62 people).
Triangles – directors; Squares - advanced students; Circles - beginning students.
Red – Spain; Black – Portugal; Blue – Venezuela; Grey – Mexico; Pink - other places (USA, Denmark, and Colombia).

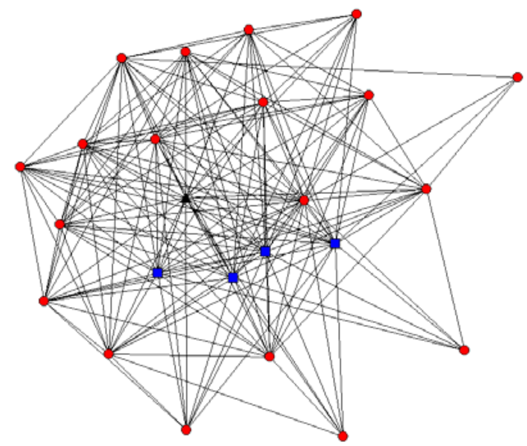

Figure 2. EB social network (24 people)
Blue squares – teachers; Red circles – students.

The network diagram of UPC community shows a cohesive network (density = 0.191) with no isolated subgroups except a single individual (he answered KIWI gathering tool several times informing that there were no interactions). The average distance between people was 1.973, reflecting that most people were just one person apart. Inside community, there were distinct levels of activity, with individual's network size varying from 0 to 50 contacts. Above 25% of community's members had more than 15 people in their individual network, and other 25% of members had less than 3 people in their individual network. Directors (triangles) were in network centre and showed highest degrees of interaction with a mean average of 21.2 contacts. If we only consider the connections between students, the density of this sub-network decrease to 0.125, showing that directors have a major role in connecting students across all community.

In the EB community, the individual mean average was 7.78 interactions by person by week (SD=3.24). Figure 2 displays the social network registered by the twenty four members during the 8 week field study. Teachers are represented by blue squares and students by red circles.

The network diagram shows an extremely cohesive network (density=0.638) with an average distance between people of 1.362, reflecting a great proximity between people. Individual's network size varies from 4 to 23 contacts, revealing a wide range of behaviors. The average number of individual's contacts is 13.42 for students and 19.25 for teachers. Considering only the connections between students, the density of students' sub-network is 0.491. This shows that, despite the higher teachers' number of contacts, students' sub-network continues being an extremely cohesive structure.

Associations between network centrality measures and individual performance

Descriptive statistics and correlations among study variables in respecting to each community students' group are reported in Table 1. We found out positive associations between degree centrality and individual's performance, with coefficients of .62 ($p < .01$) for UPC group and 0.57 ($p < .05$) for EB group. These results support the first hypothesis under study, confirming that in both communities studied, the greater the number of contacts of a student the better is his or her performance.

Regarding the relation between closeness centrality and performance, the results show negative associations with coefficients of -.67 ($p < .01$) for UPC group and -.57 ($p < .05$) for EB group. These results indicate that the shorter the distance of one individual to all others in community, the better is his or her performance, giving support to second hypothesis under study.

Table 1. Descriptive statistics and correlations for study variables in students' groups

		Mean	SD	1	2	3	4
UPC (n=46)	1. Degree	10.43	6.50	1			
	2. Closeness	750.65	14.47	-.87**	1		
	3. Betweenness	14.82	28.51	.56**	-.37*	1	
	4. Performance	2.95	1.25	.62**	-.67**	.23	1
EB (n=15)	1. Degree	14.27	4.33	1			
	2. Closeness	55.73	4.33	-1**	1		
	3. Betweenness	2.89	4.23	.70**	-.70**	1	
	4. Performance	12.23	2.38	.57*	-.57*	.17	1

** $p < .01$;
* $p < .05$.

Results did not support our third hypothesis which stated that betweenness centrality is positively related to individual performance, unlike referenced by some studies (Tsai & Ghoshal, 1998; Cross & Cummings, 2004; Burt, 1997 e 2005; Song *et al*., 2007). Apparently, in these two communities, the fact that an individual is occupying a more central role in the interconnection among others has no relation with his or her performance.

Conclusions

Our work led us to some interesting results showing that in the two distributed learning communities there were significant correlations between the social network and students' performance. This indicates that some students were structurally advantaged or disadvantaged as a result of their network positions. Through the correlation analysis between centrality metrics and individual performance, it was possible to verify the association between degree centrality and performance, revealing that the greater the number of contacts of an individual, the better is his performance. It was also possible to verify the significant association between closeness centrality and performance, which reveals that the shorter the distance from one individual to all other individuals in the community, the better is his performance. We found no relation between an intermediation position among others and individual performance which may be due to the high cohesion and density of both communities' networks.

These results seem to confirm the relevance of using these metrics for supporting knowledge management and make a contribution to the clarification of the concept of social capital in this type of communities. Despite the great amount of distance communication existing and although the distinct objectives and working methods of each community, results showed that social structure is related to performance. Social network analysis can be conducted as a means to identify and understand emerging social structures and collaborative patterns, which in turn might give helpful clues to managers and teachers, allowing them to act and propose different strategies when trying to redesign social infrastructures in distributed learning communities. We also believe that this kind of information about social network could be a powerful tool to students. Based on Burt and Ronchi (2007) field experiment, in which the performance of the executives educated in the network structure of social capital showed to improve in comparison to a control group, it is possible that enhancing students' awareness about social structure can have potential effects on their performance.

Limitations

This study has some potential limitations that should be acknowledged. The first concerns the validity of our performance measures. In EB community we use formal grades that may not represent comprehensively the student's performance and his/her contribution to community, such as the degree of initiative and cooperation. Odelius and Santos (2007) argue that an evaluation process of individual's performance, which they see as the measurement of aspects of individual's competitiveness, effectiveness, efficiency and skills, should be conducted assessing gains for the individual and the organization. Moreover, in addition to meeting the gains in productivity, this assessment should also consider the prospect of personal and professional growth. In UPC community performance's measures could be distorted if director's perceptions were inaccurate and although performance ratings data had different sources, aspects of the social context may have biased the subjective evaluation of performance.

Another limitation that deserves to be pointed out concerns the fact other variables that could influence social networks' structures and patterns were not included. Subjects' attributes and characteristics, such as students' context activity, being full or part time student, training bases, or number and type of projects, may eventually influence social network's position and student's performance. Moreover, according to Cross and Cummings (2004), in knowledge intensive work contexts, interactions with the outside community are positively related to individual performance, however interactions with the outside were not considered in this study. Further research considering a wider set of variables is needed in order to assess which characteristics could have an important role in social network structure and could be related to performance.

Although we worked with two communities with different structures and different working styles and objectives, we are also cautious in attempting to generalize findings to other settings where social dynamics and structures may be significantly different. The absence of a relation between betweenness centrality and performance, unlike referenced by some studies (Tsai & Ghoshal, 1998; Cross & Cummings, 2004; Burt, 1997 e 2005; Song *et al*., 2007), despite it may be due to the high cohesion and density of these two communities' networks, deserve future and deeper research. We emphasize that findings and implications of this study should be further tested and validated by future research employing samples in different contexts.

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