Social Network Analysis Techniques: Implications for Information and Knowledge Sharing in Virtual Learning Communities

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ABSTRACT
This paper employs social network techniques to analyze patterns of interactions critical to information and knowledge sharing among learners in a virtual learning community. Drawing from the results of our analysis, fundamental variables which are more likely to affect information and knowledge sharing in virtual learning communities are explored and future research initiatives to pursue these issues is presented.

1. Introduction
Improving the ways in which learners build better connections with each other to acquire useful information and knowledge is critical to research and practice. But what are better relationships and connections within virtual learning communities, and how do we study useful relationships and connections that can provide opportunities for exchanging information and knowledge sharing? And what are the implications of social connectivity to information exchange and knowledge sharing?

This paper employs social network techniques to understanding the patterns of interactions among learners in a virtual learning community. It discusses various variables which can possibly affect information and knowledge sharing practices in virtual learning communities. This work has two key contributions to research and practice on virtual learning communities. First it presents social network techniques as a way of understanding the flow of information and knowledge in order to understand better connections in virtual learning communities. Second, we explore fundamental variables which are more likely to affect information and knowledge sharing. We believe knowledge drawn from these two contributions can inform the design of tools and process to support effective interaction and knowledge sharing in virtual learning communities.

2. Related Work
Knowledge and learning are social phenomena embedded in human interactions. In virtual learning communities settings, learning involves sharing knowledge, exchanging information and these require participation and contributing to the community, sharing, exploring, and deploying a collective knowledge base [21][20]. Research reveals that in community settings, people learn as they navigate to solve problems together [13] or design representations of their understanding [28]. Much learning between and within communities occurs with boundaries rich in interactions, whether formal, informal, or through a computer based system [32]. Similarly, the processes of learning in virtual learning communities also can be improved if different actors are known.

In virtual learning communities, where learners are often isolated from each other, and their instructor, knowledge sharing is fundamental to effective learning. But promoting knowledge sharing requires understanding the
social relationships and connections that are critical to information and knowledge sharing.

Before exploring these issues further, we discuss the notions of knowledge, information and data within virtual community settings. In addition, we describe the difference between knowledge and information, and distinguishing between knowledge sharing and information exchange. Andriessen [1] suggested that information is basically a collection of facts and figures, while knowledge consists of insights and interpretations, is personalized and refers to specific situations.

Different kinds of knowledge can also be identified, interpersonal knowledge normally consisting of personal insights, intuitions, experiences and competence and community knowledge which can be in the form of documents, databases, books, memos etc.

Though the distinction between interpersonal and community knowledge help us to understand what can easily be shared and what can not, there is no agreed upon standard definition of knowledge. However, Polanyi’s [22] distinction between tacit and explicit knowledge has gained widespread acceptance. We suggest that this distinction has implications for knowledge sharing within virtual learning communities.

In Table 1, we distinguish between tacit knowledge and explicit knowledge. Sharratt and Usoro [27] suggested that knowledge sharing is a process whereby a resource is given by one party and received by another. Although based on the knowledge of the source, the knowledge received cannot be identical as the process of interpretation is subjective and is framed by our existing knowledge and our identity [7].

Knowledge is constructed in different kinds of virtual communities primarily through negotiation. The knowledge sharing process in virtual learning communities entails an exchange of experiences exchanged through storytelling. Storytelling can be effective techniques for conveying information in a compelling and memorable way. Neal [17] noted that storytelling remains an important mode through which individuals and cultures communicate. When learners share experiences, their engagement can be high after all they share common problems and seek for common solutions to the problems.

Further, when learners of similar experiences exchange stories they are likely to build a rapport and special bond that connects them together regardless of their adverse differences. Quite often in learning environments, learners carry their expectations prior experiences and knowledge with them, and learn by relating stories they hear to their own experiences. Indeed, stories are important cognitive events of a particular pedagogical value because they encapsulate in one rhetorical package, four of the crucial elements of human communication: information, knowledge, context, and emotion [19] [17]. Knowledge is the combination of information, context, and experience, and while there is no agreed upon standard definition of knowledge, knowledge can be conveniently classified as either tacit or explicit (see Table 1). Nonaka and Takeuchi [18] have provided an elegant characterization of knowledge conversion processes connecting tacit and explicit knowledge sources (Figure 2). Tacit knowledge can be defined as knowledge which is personal, experiential and context specific. Explicit knowledge on the other hand is knowledge that can be codified, articulated and published in some way.

Table 1. Comparative characteristics of tacit and explicit knowledge [7].

<table>
<thead>
<tr>
<th>Tacit Knowledge</th>
<th>Explicit Knowledge</th>
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<tbody>
<tr>
<td>• Desired from experience and is the most powerful form of knowledge</td>
<td>• Can become obsolete quickly</td>
</tr>
<tr>
<td>• Difficult to articulate formally</td>
<td>• Formal articulation possible, and can be processed and stored by automated means, or other means</td>
</tr>
<tr>
<td>• Difficult to communicate and share</td>
<td>• Easily communicated and shared</td>
</tr>
<tr>
<td>• Includes privately held insights, feelings, culture and values</td>
<td>• Formally articulated and public</td>
</tr>
<tr>
<td>• Hard to steal or copy</td>
<td>• Can be copied and imitated easily</td>
</tr>
<tr>
<td>• Shared only when individuals are willing to engage in social interaction</td>
<td>• Can be transmitted</td>
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</table>

Tacit and explicit knowledge are common to all kinds of communities but the protocol for transmitting each one of them differs from one community to another. For instance, in virtual learning communities, the knowledge construction process can involve continuous reciprocal engagement in exchange of information and knowledge sharing and other kinds of social process (see Figure 1). When learners exchange data, the data is processed into information. In turn, information can be situated in a particular context and turned into knowledge for a particular individual.

How specific knowledge is generated from data and information depends on how the data are stored, and how information is presented, organized, communicated and received by particular individuals in a particular community. Sharing knowledge is mostly achieved through tacit to tacit communication, though clearly
knowledge sharing can also be achieved through the tacit to explicit to tacit conversion loop [14].

Figure 1. A process model for knowledge construction in virtual communities [7]

Moreover, the way data are shared or information is presented and communicated depends on specific or general sets of protocols available in a particular community. In addition, an individual’s cognitive processes determine how information is processed into knowledge. The cyclical process in figure 1 implies that knowledge is both an input and product in itself. In other words, what constitutes knowledge for one individual might be information for another individual, and what counts as information for another individual in a specific time might become data later.

In order to understand information flow and knowledge sharing, we employed social network analysis (SNA). SNA is the study of mathematical models for interactions among people, organizations and groups. According to SNA theory, social relationships are viewed in terms of nodes and ties. Nodes are individual actors within the network, and ties represent the flow of relationships between the actors. These relations defined by linkages among units/nodes are a fundamental component of SNA [31] [27].

Historically, research in the field has been led by social scientists and physicists [15] [31] and previous work has emphasized binary interaction data (see table 2), with directed and/or weighted edges. There has not, however previously been significant work by researchers in statistical natural language processing, nor analysis that captures the richness of contents of the interactions—the words, the topics, and other high dimensional specifics of the interactions between people. Using pure network connectivity properties, SNA often aims to discover various categories of nodes in a network. Using network properties in SNA we can assign “roles” to certain nodes, e.g. [15] [33].

In the context of the web, development of evolution models and properties of random walks, mixing rates and Eigen systems have all contributed to the social network analysis as a data mining approach especially in web settings [3][4][16]. In web applications, Google uses the social network algorithms to build its search engine. Some of the measures the search engine uses to search, rank and retrieve information are the notion of prestige and centrality measures.

The shape of the social network helps to determine a network’s usefulness to its individuals. For instance, smaller and tighter networks can be less useful to their members than networks with lots of loose connections (weak ties) to individuals outside the main network. Moreover, networks, with many weak ties and social connections, are more likely to introduce new ideas and opportunities to their members than closed networks with many redundant ties. In other words, individuals who have similar knowledge, interests, and personal attributes can easily connect and share knowledge. And those individuals with connections to other network are likely to have access to a wider range of information and knowledge.

3. Research Context

We conducted content analysis of online interactions in a six credit graduate course in Educational Communications and Technology at a western Canadian university. Each year, the course spanned over two entire semesters. The course was blended online and face-to-face. The content of course was on theoretical and philosophical foundations of educational technology and the principles and practices of instructional design. While most students were able to attend the group meetings regularly, class cohorts had members who participated exclusively or mostly from a distance.

Given the blended nature of the course, and the fact that the course is often populated by mature and motivated students, we confine our conclusions to similar environments, and acknowledge that these results cannot be generalized to environments that are entirely online, entirely face-to-face, or comprised of different types of students and content domains.

In addition to the content analysis of the discourse transcript analysis, a follow up survey instrument with 30 items was administered to a
random sample of nine of the fifteen graduate students who participated in the course.

4. Results
We conducted the transcript analysis to analyze the exchange of messages within the group and to examine the degree of connectivity of each individual within the community. The degree of connectivity was established and presented in a form of a binary matrix (see table 2). Further, there was 100% response rate to the survey. Of those who responded, 56% were female and 44% male. Little diversity in language differences among participants was observed. The majority about 90% indicated English as their first language and 10% indicated other languages. In terms of prior training, the majority of the participants identified themselves as teachers, with bachelor degrees in education and other degrees in different domains covering the social sciences and humanities as well as natural sciences.

Further, diversity in professional affiliation was observed, ranging from schoolteachers 56%, instructional designers 11% and others such as technology-co-coordinators, administrators and private consultants 11%. Though there was a considerable difference in professional affiliations, most of the participants shared common background training and there was a little difference observed between men and women in the sample. Space does not allow us to fully elaborate on the details of results of the survey in this paper, however, key highlights of the results as they relate to information exchange and knowledge sharing are discussed later in the paper.

4.1 Social Network Analysis
In order to visualize the patterns of interaction among the participants, we codified interactions into a two dimensional matrix. A matrix of a network of size \( n \times n \) is a square matrix whose elements represent ties (links) among individuals or agents in a given network.

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Table 2. Binary Matrix Showing Engagement

The network is presented as a graph with nodes representing individuals and ties/links representing relationships among them based on a relational data model. The relational dimension between nodes \( A \) and \( B \) is recorded as 1 in the cells \((A, B)\) and \((B, A)\) if a tie is present between them; and as 0 if there is no tie. In other words, if the relation is directional, an arc (flow) from source A to link B and vice versa is recorded as 1 in cell \((A, B)\), and a 0 in cell \((B, A)\), this is also referred to as adjacency. Adjacency is the graph theoretic expression of the fact that two agents, represented by nodes, are directly related, tied, or connected with one another (Robinson & Foulds, 1980). Formally it is presented as:

Let \( n_i, n_j \in \mathbb{N} \) denote agents i and j in a set of N agents. Let \( a_{ij} \) denote the existence of a relation (arc) from agent i to agent j. Agents i and j are adjacent if there exist either of the two arcs, \( a_{ij} \) or \( a_{ji} \). Given a graph \( D = (N, A) \), its adjacency matrix \( A(D) \) is defined by \( A(D) = (a_{ij}) \), where \( a_{ij} = 1 \) if either \( a_{ij} \) or \( a_{ji} \), and 0 otherwise.

The number of arcs (links) beginning at a node is called the outdegree of the node. And they suggest connections, and in our case initiation of engagement or discourse. Outdegree is measured as the row sum for the node in a dichotomous matrix: outdegree of actor i = \( \sum_j a_{ij} \) (1). The number of arcs ending at a node is called the indegree of the node, indicating the reception of engagement. The column sum (for a node) in a dichotomous matrix measures the indegree of the node: indegree of actor j = \( \sum_i a_{ij} \) (2). Wasserman and Faust (1994) suggested that a node is a transmitter if its indegree is zero and its outdegree is non-zero. A node is a receiver if its indegree is non-zero and its outdegree is zero, and it is isolated if both indegree and outdegree are zero.
Using UCINET 6 software [2] we generated a network (see graph 1), composed of 15 actors/nodes ($N=15$) with connections indicating the flow of interactions to determine the flow of information and knowledge sharing.

Graph 1. Visual patterns of connectivity in the community.

The criterion used for constructing the SNA graph shown above is based on graph theoretic expression [23]. The graph represents a directed graph with arrows indicating interaction and engagement between nodes (individuals) in the community. For example, if $x$ sends messages to $y$ and $y$ does not send back any messages, then there is no reciprocal relationship between the two $x$ and $y$ and this is indicated in the graph with blue links. Meanwhile if’s reciprocal relationship exists; it is depicted in red, suggesting a two-way communications.

Social network researchers often measure network activity for a node by using the concept of degrees—the number of direct connections a node has. In SNA the notion of degree suggests the number of connections an individual has in the network. Freeman outdegree and indegree measures are some of the most commonly used degree of centrality used for various reasons. In this study we employed Freeman’s indegree and outdegree measures to determine the number of connections among individuals in the community. Indegree reveals the number of individuals who have read messages in the community. Outdegree measures the number of messages an individual has sent to all other individuals in the community. In graph 1 the links indicate engagement between nodes (individuals) in the community. A single-edge link suggests one-way communication (when $A$ sends mail or a message to $B$ but $B$ did not respond to $A$) while a double-edge link suggests two-ways communications. Table 3 summarizes the results of the in-degree and out-degree measures.

Table 3. The Degrees of Connectivity among nodes in the Network

<table>
<thead>
<tr>
<th>Node</th>
<th>Outdegree</th>
<th>Average</th>
<th>Indegree</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rk</td>
<td>109</td>
<td>0.9</td>
<td>18</td>
<td>0.03</td>
</tr>
<tr>
<td>Dm</td>
<td>24</td>
<td>0.04</td>
<td>12</td>
<td>0.02</td>
</tr>
<tr>
<td>Bn</td>
<td>67</td>
<td>0.11</td>
<td>79</td>
<td>0.13</td>
</tr>
<tr>
<td>Dna</td>
<td>25</td>
<td>0.04</td>
<td>39</td>
<td>0.06</td>
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<tr>
<td>De</td>
<td>54</td>
<td>0.09</td>
<td>56</td>
<td>0.09</td>
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<tr>
<td>Di</td>
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<tr>
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<td>Dn</td>
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<td>Jf</td>
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<td>Jn</td>
<td>59</td>
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<tr>
<td>Rn</td>
<td>7</td>
<td>0.01</td>
<td>33</td>
<td>0.06</td>
</tr>
</tbody>
</table>

The degree of centrality in social network theory is the most intuitive network conceptualization of centrality, and it has a simple theoretical relationship with accuracy. The centrality of an individual is simply the number of people that person is directly tied to. A node with a high degree of centrality suggests a high proportion of connectivity with other nodes in the network. This was measured by either the number of messages an individual sent to others or received from the other members of the community. The total number of messages a person sent to members of the community shows their outdegree centrality. For example, in Table 2 RN has the lowest outdegree of centrality, meaning that s/he sent out only 7 (see node in grey color in the graph) messages compared to Rk who has a high proportion of outdegree centrality (109), with a bigger node in the graph colored red.

Indegree, on the other hand, shows the number of messages a person has received from other members of the community. In Table 2, Bn
has the highest indegree of centrality (79), with a node colored green in the network, followed by Jn (74), (see node in the graph colored yellow) compared to DM who has only 12 (which implies, she has only received a total of 12 messages from others in the community). In Figure 1 we show the proportions of the distribution of indegree and outdegree measures among all the members of the network.

Figure 1. Distribution of indegree and outdegree measures of centrality in the sample.

In figure 2, Rk displays a high outdegree than indegree of centrality. A high outdegree of centrality in the network suggests that a ctor has sent out more information to others in the network. It also implies that an actor has the possibility of influencing other actors in the network through multiple channels of communication. For example, Rk's position is regarded as the most influential in the network.

In contrast, peripheral actors maintain few or no connections with others and thus are located at the margins of the network. Rn who has a relatively low proportion of outdegree centrality, can be considered a spectator or “lurker”. However, lurkers in social network terms are not necessarily unimportant. In fact they can maintain an important location measured in terms of “prestige”, suggesting that they are recipients of many directed ties, but initiate few relationships. In other words, they do not reciprocate.

A node’s prestige in a network is essentially its reputation or influence arising from success, achievement, rank, or other favorable attributes of that individual node. Nodes with high prestige are important or prominent nodes and they are those that are linked or involved with other nodes extensively. In practical sense a node with extensive connections (links) or communications with many other nodes in the network is considered more important than a node with relatively fewer connections.

Prestige is a more refined measures of prominence of an actor that centrality measure. The differences between prestige and centrality are that prestige focuses on indegree connections while centrality deals with out degree. The simplest measure of prestige of an actor $i$ in a network (denoted by $P_D(i)$) is in fact its indegree of connectivity and it is given by:

$$P_D(i) = \frac{d_1(i)}{n-1} \ldots \ldots \ldots \ldots (3).$$

Where $d_1(i)$ is the indegree of $i$ (the number of indegree connectivity of actor $i_1$) and $n$ is the total number of nodes in the network. Similar to centrality, dividing $n-1$ standardizes the prestige value to the range from 0 and 1. The maximum prestige value is one when every other node links to $i$.

We think that the measure of prestige of a node can be extended to examine the source of the connecting nodes as well as the content of the information itself. Examining the direction of connectivity and the nature of the connectivity can reveal the significant importance of the message as well as the status of the node sending and the one receiving the information. For instance in a learning environment, if $A$ is a competent and knowledgeable individual in the network, and imagine $A$ interacts with $B$ then it is more likely that $B$ is likely to acquire useful information from $A$ and hence, both $A$ and $B$ can share important status in the network.

There are other related measures of prestige including identification of cliques through mutuality; implying the degree to which all nodes in the network are mutually connected to each other. We suspect that in virtual learning communities, several reasons can be attributed to mutuality of connectivity among nodes. For instance nodes that share interests, have common goals, are of the same gender, language, profession etc are likely to mutually connect to each other and form a clique in the network. Distant can also be used as a measure of prestige entailing the degree to which one node is connected to other nodes of significant importance. For instances, nodes that are very close to nodes of high prestige are likely to have access to status in the community compared to those in a distant. Important or prominent actors are those that are linked or involved with other actors extensively.

To determine whether a community formed out of the interaction, we determined group
density. Density is a measure of how connected individuals are to others in a group, and the idea is that a higher degree of connection is a positive indicator of community. A group’s density is “the ratio of the actual number of connections observed, to the total potential number of possible connections [9].” It is calculated by using the following formula: Density = 2a/N (N-1), where "a" is the number of observed interactions between participants, and "N" is the total number of participants. Outdegree density was calculated to be 5.54 revealing fair distribution of messages sent out, in the indegree density was calculated to be 5.64. However, the measure of density is sensitive to the size of the network, so larger groups will likely exhibit lower density ratios than smaller groups [9].

5. Discussion and Implications
In social network graph applied to virtual learning community settings, a tie or relation between two actors has both strength and content. The content might include information, advice, or friendship, shared interest or membership, and typically some level of trust. The level of trust in a tie is crucial in virtual learning community. Two aspects of social networks affect trust. One is “relational”—having to do with the particular history of that tie, which produces conceptions of what each actor owes to the other. The other is “structural”: some network structures make it easier than others do for people to form trusting relationships and avoid malfeasance. For example, a dense network with many connections makes information on the good and bad aspects of one’s reputation spread more easily.

One of the key motivations to employ social network analysis to understand interaction patterns which are more likely to promote “a sense of a community” in online learning environments. A sense of a community emerge when people interact in a cohesive manner, continually reflecting upon the work of the group while always respecting the differences individual members bring to the group [10]. Previous research suggests that students can experience a sense of a community online if the environment is intentionally structured and nurtured and when certain fundamental variables are addressed including, trust, awareness of various personal and community aspects, social protocols and reciprocal relationships [5][24].

These variables are critical to examine when understanding the flow of information and knowledge sharing in the community. For example, trust and awareness can greatly influence people’s willingness to productively engage with each other in exchanging of useful information and sharing of personal experiences. People share knowledge with those whom they know and feel they are trust worthy and can not use their knowledge inappropriately, and are willing to share or reciprocate with others in the future.

Trust can also encourage knowledge sharing when people are aware that they share common goals and common values. However, when people do not share common goals and values, a sense of a community is not likely to develop, and the self-interest of high status people is likely to predominate. In other words, people who feel they possess more power are likely to use it inappropriately [24].

In terms of sharing tacit knowledge, if the recipient of knowledge is not aware or convinced that the source is competent and trustworthy [5] it is unlikely that knowledge from that particular individual will be accepted [12]. On the other hand, if the owner of the knowledge is not confident or does not trust the seeker of the knowledge to reciprocate in the near future, they may choose to hoard their valuable knowledge. Even the sharing of explicit knowledge in this instance depends on the willingness of the individual to connect to others and participate in the community.

Further, results from the survey revealed that in a virtual learning community, a sense of a community can be sustained through maintenance of proper social protocols, capable of enhancing reciprocal relationships. Reciprocal relationships provide people with the willingness and confidence to invest in collective or group activities, knowing that others will reciprocate in future interactions.

Participants also indicated that social networking among themselves helped nurtured their sense of community. They suggested that social networking usually provided better information exchange, knowledge sharing and better learning opportunities. In addition, they also mentioned that better social connections lead to more effective interaction and productive discourse throughout the course.

It seems participants’ experiences in building social networking helped them to build and sustain better relationships with other members of the course beyond the end of the course.

Better connections can strengthen better social relationships, which in turn can enable
individuals to effectively exchange tacit knowledge. Tacit knowledge is an intangible resource that exists within the mind of the individual [29]. Both information and knowledge are grounded on data. The two can be differentiated if we consider interpretation and meaning. Information by definition is informative and, therefore, tells us something. It is data from which we can derive meaning. Knowledge is directly related to understanding and is gained through the interpretation of information. Knowledge enables us to interpret information i.e. derive meaning from data. The interpretation of meaning is framed by the perceiver’s knowledge. So what one person perceives as information can equate to meaningless data to another [26].

So information that is interpreted generates meaning and new knowledge. Thus, information can be added to knowledge to increase what is known. Knowledge can be derived from both information and data since one needs to know the context of data before it can be interpreted as information [7] [26].

The motivation to share knowledge in virtual learning communities is affected by various factors. From the survey data, we present some of the most Key results from the survey indicated that knowledge sharing in virtual learning communities can be influenced by trust, different forms of awareness and social protocols. The results also suggest that there are various reasons why people in general would not engage in knowledge sharing in virtual learning communities. These are summarized as follows:

- People are mostly unwilling to share knowledge with people they hardly know
- People would not reveal their information if they do not trust the recipient
- People would not share knowledge in an environment where competition instead of co-operation is encouraged and one in which the notion of “knowledge is power” is maintained
- People can resist new knowledge if it is not encouraged or created from within
- Doubt is another possible reason for not sharing, for instance, if an individual is not sure their knowledge would be used in an appropriate context, misapplied and possible blame of failure on them, or if they suspect that others will dishonestly claim ownership
- In circumstances, where knowledge sharing is voluntary and there is increasing lack of time, people are more likely to withdraw from knowledge sharing activities
- In professional communities such as distributed communities of practice, if there is inadequate technology for engagement, reliability, security, and safety, people can withdraw from participation [6]
- Providing incentives (especially monetary) as reward motivations for encouraging knowledge sharing is found to be ineffective[1] other more implicit rewards such as self-actualization and recognition seem to be more effective instead
- Ignorance and lack of self-confidence is another possibility for with-holding information that can benefit others, especially in situation where individuals are not aware that their knowledge can contribute to others
- Knowledge sharing would not occur if the technological environment can not encourage the transfer of tacit knowledge [11]

Social network is a useful approach for analyzing the flow of information and knowledge in a virtual learning community. However, it is clear that network properties are not enough to discover all the roles individuals can play in a social network. Currently we are considering the possibility of employing various social network metrics to understand the flow of information and knowledge sharing in sparsely connected as opposed to densely connected network.

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6. REFERENCE


