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Identifying Peer Interaction Patterns and Related Variables In Community-Based Learning

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Abstract. The purpose of this study was to investigate patterns of peer interactions and to identify the relationships of peer interactions with learner characteristics and learning outcome in community-based learning. The participants were 24 middle school students joined in an online learning community for a week. Two patterns of peer interactions such as in-degree and out-degree centrality were identified. Students with high intra-personal or verbal-linguistic intelligence were related to high in-degree centrality, while students with high interpersonal intelligence or prior knowledge were related to high out-degree centrality. That means "self smart" or "word smart" students were popular and played knowledge broker's roles in their community. On the other hand, "social smart" students or "high prior knowledge" students were open and friendly activators and delivered vast information. Moreover, higher peer interactions were related to better learning outcome. These results indicated that peer interactions were important intervening variables to enhance learning effect.

Keywords: Community-based learning, peer interaction, learner characteristics, social network analysis

INTRODUCTION

With the rapid development of a knowledge-based society, it is of growing importance to create knowledge through collaboration with others beyond the individual. Recently, with the expansion of online communities, community-based learning has brought new learning methods where learners form communities around common objectives and create knowledge through interaction with other members (Bielaczyc & Collins, 1999; Palloff & Pratt, 1999; Rovai, 2003; Wilson & Ryder, 1998). However, research in community-based learning has been limited to conceptual and macroscopic studies such as the process of learning community development.

Therefore, we need to identify peer interaction patterns and relationships among the variables that promote peer interactions and learning effects in community-based learning. Thus, the purpose of this study was to investigate patterns of peer interactions and to identify the relationships of peer interactions with learner characteristics and learning outcome in community-based learning. The contribution of this study may provide practical guidelines for designing and operating strategies to enhance the effect of community-based learning.

THEORETICAL BACKGROUND

Community-Based Learning

General collaborative learning describes an instructional approach in which students work together in small groups to accomplish a common learning goal. Collaborative learning is based on these principles: (1) Tasks are carefully designed to be suitable for group work. (2) There is positive interdependence. (3) Students are individually accountable for learning and participation. (4) Attention and class time are given to interpersonal/collaborative skill building. (5) The role of the teacher changes from being "an instructor" to "a guide or a facilitator" (Johnson & Johnson, 1999). On the other hand, community-based learning is a learner-centered approach and based on the principles of collaborative knowledge construction and learning community. Students within the learning community set up common goals, generate ideas collaboratively, and share their production (Wilson & Ryder, 1998).

The process of community-based learning consists of five phases (figure 1). (1) Common goals assignment phase: students set up common goals and tune up member's demands and interests. (2) Group rules forming phase: students make group rules and distribute roles among members. (3) Assignment recognition phase: students recognize the problem of individual interests and experiences and carry out inquiry through discourse. (4) Collaborative accomplishment phase: students accomplish various collaborative activities such as intra-group and inter-group collaboration and interact with external specialist. (5) Production generation phase: students generate and share final production and also carry out peer evaluation and subsequent activity (Palloff & Pratt, 1999). Table 1 indicates five components of community-based learning environment include in collaborative learning, social interaction, planning & reflection, knowledge base, and evaluation & compensation (Kang & Byun, 2001; Stahl, 2000).

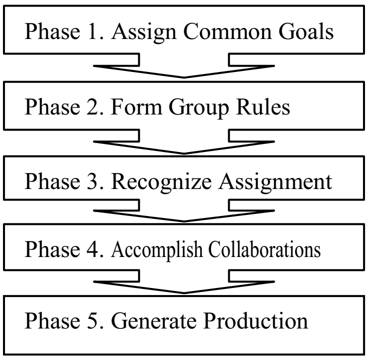

Figure 1. The process of community-based learning

Table 1. Five components of community-based learning environment

Dimension	Description	Function
Collaborative Learning	Exchange opinions and interact with members during group work	discussion, whiteboard, group workplace, communication tools, etc.
Social Interaction	Informal communication and recreation	free-board, announcement, Q/A, etc.
Planning & Reflection	Identify personal and group goal, plan time schedule for project, divide member' roles, and reflect learning process	reflection note, schedule, goal/ role specification, etc.
Knowledge Base	Share and Store learning resources and products	e-library, mybase, teambase
Evaluation & Compensation	Peer evaluation, instructor evaluation, internal/external compensation	evaluation rubrics, comment form, avatar-point, etc.

Learner Characteristics: Prior Knowledge & Three Personal Intelligences

This study included four learner characteristics: Prior knowledge, verbal-linguistic intelligence, interpersonal intelligence, and intra-personal intelligence. The reason why they were selected that students need to have abilities to learn through knowledge sharing, dialogical conversation skills, self-regulation ability, and interpersonal skills for enhancing student's learning effect in an online learning community (Bielaczyc & Collins, 1999; Jonassen & Land, 2000; Palloff & Pratt, 1999; Stahl, 2000).

Prior knowledge means that the individual already has knowledge regarding the problem or assignment. By reviewing previous literature, prior knowledge greatly affects the accomplishment process and achievement. Gardner's theory of multiple intelligences applied within K-12 and higher education research and practices and also described the way of learning styles (Gardner, 1999). According to a multiple intelligence approach, students with high verbal-linguistic intelligence ('word smart') learn best through language including speaking, writing, reading, and listening and have high achievement and good communication skills. Student with high interpersonal intelligence ('social smart') learn best through interaction with other people such as discussions, cooperative work, or social activities and enhance a friendly atmosphere and cohesiveness in groups. Students with high intra-personal intelligence ('self smart') learn best through meta-cognitive practices such as awareness of their feelings, self-reflection, thinking processes, and their own strengths and weaknesses. Self-smart students are good at end-goal setting, goal pursuing, and process assessment (Armstrong, 1994; Gardner, 1999).

Interaction Analysis: Social Network Analysis

Social network analysis is a sociological research tool. We can schematize social structure to a network composed of the link that connects a node to a node (node: participant, link: relation). Up to date, social network analysis appeared to apply a useful tool for analyzing participant interaction in the e-learning (Haythornthwaite, 2002; Palonen & Hakkarainen, 2000). It provided a new kind of in-depth information on communication relations, power relations, participant's role, and so on. Degree centrality of social network analysis was used as an instrument for analyzing the participant's interaction level and direction in this study.

In-degree Centrality & Out-degree Centrality

Degree centrality indicates the density of relationships between participants in a network and is presented by in-degree centrality and out-degree centrality (Figure 2).

A's In-degree Centrality = $\dfrac{\text{In-degree of A's connection}}{\text{Participants-1}}$	A's Out-degree Centrality = $\dfrac{\text{Out-degree of A's connection}}{\text{Participants-1}}$

Figure 2. Formulas of degree centrality

In-degree centrality means the degree of relations that behavior A receives the message from others in communication situations. Students with high in-degree centrality have more interactive activities for receiving information or comments from others. They are popular students or knowledge broker in their community.

On the other hand, out-degree centrality means the degree of relations that behavior A sends the message toward others in communication situations. Students with high out-degree centrality are more active in providing information to others in discussion or providing comments to other's opinions. They prefer to link open and friendly human relations to many participants and have important role to delivery information and data in their community.

METHODOLOGY

The subjects of this study were 24 first and second year middle school students joined in an online learning community operated by N company. The students accomplished a task that examined Greek-Roman mythology for one week. Based on a literature review of the process in community-based learning and previous studies on group interactions variables, a research model consisted of the input, process, and output variables: the input variables were four learner characteristics such as prior knowledge and three intelligences (verbal-linguistics, interpersonal, and intra-personal); the process variables involved two interactions such as in-degree centrality and out-degree centrality); the output variable was individual achievement.

The research instruments used in conducting the experiment were community-based learning environments, a learning task, prior knowledge test (Spearman-Brown formula / r = .66), multiple intelligence test (verbal-linguistic / interpersonal / intra-personal intelligence) (Cronbach's alpha = .67~.85) (Moon et al., 2001, adapted by Shearer, 1996), interaction analysis tools (social network analysis), and achievement evaluation rubrics (Wen, 1998). Data was gathered for a week and analyzed by social network analysis on interaction pattern using Netminer 2.0 tool and path analysis of learner characteristics, peer interaction, and learning outcome. Path coefficients were used as standardized regression coefficients (beta).

RESULTS

Peer Interaction Patterns Using Social Network Analysis

In-degree centrality of peer interaction

Figure 3 indicates that students s20(f), s17(f), s2(m), s3(f), s6(m), and s9(f) had higher in-degree centrality of interaction and positioned toward the center of the in-degree centrality circle. They received information or comments from others actively and were popular students and knowledge brokers in their community.

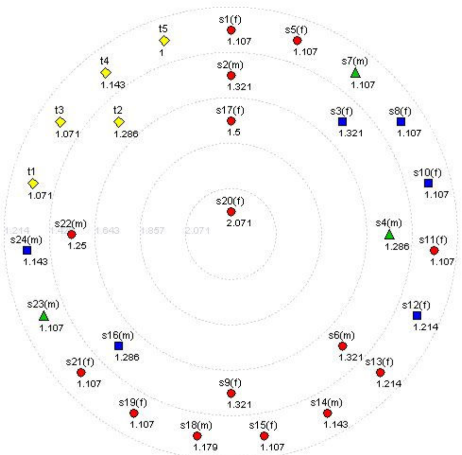

Figure 3. Social network analysis graph on in-degree centrality

s: student, t: mentor, (f): female, (m): male
Attributes: Verbal-linguistic intelligence
● : high (80~100 score) ■ : middle (60-79 score)
▲ : low (1~59 score) ◇ : mentor

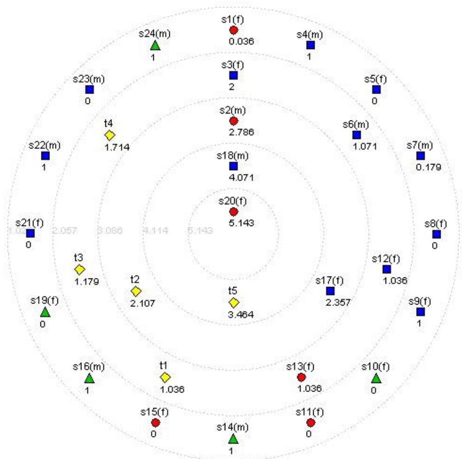

Figure 4. Social network analysis graph on out-degree centrality

s: student, t: mentor, (f): female, (m): male
Attributes : Prior knowledge
● : high (90~100score) ■ : middle (60~89 score)
▲ : low (1~59 score) ◇ : mentor

On the side of individual attributes, highly intrapersonal intelligent students (s2(m), s9(f), s17(f), etc.) or high verbal-linguistic intelligent students (s2(m), s9(f), s17(f), s20(f), etc.) (figure 3) had higher in-degree centrality. In addition, s2(m) and s20(f) students were not only high intrapersonal and verbal-linguistic intelligence but also high prior knowledge students. On the side of relational property, middle and high intrapersonal or verbal-linguistic students dominated in-degree interaction within this learning community. Furthermore, s3(f), s9(f), and s20(f) students interacted with mentors (t2, t4, t5) as well as peers actively.

Out-degree centrality of peer interaction

Figure 4 indicates that students s20(f), s18(m), s2(m), and s17(f) had higher out-degree centrality of interaction and positioned toward the center of the out-degree centrality circle. They actively participated and provided information and comments to other's opinions actively. They also linked human relations to many participants and have important roles in delivering information and data in their community.

On the side of individual attributes, middle and high interpersonal intelligent students (s2(m), 17(f), 20(f), etc.) or middle and high prior knowledge students (s2(m), s17(f), s18(m), s20(f), etc.) (figure 4) had higher out-degree centrality. On the side of relational property, middle and high interpersonal intelligence or prior knowledge students dominate interaction within this learning community. Moreover, students s2(m), s18(m) and s20(f) interacted with mentors (t2, t4, t5) actively

Meanwhile, two mentors (t2, t5) appeared to have high out-degree centrality. They connected with many students and provided students with guidance and information. In particular, students s2(m), s17(f), and s20(f) were higher out-degree centrality as well as higher in-degree centrality. The correlation of in-degree centrality and out-degree centrality was high (Kentall's tau τ =.796, p < .05, n = 24). However, students receiving many messages were not necessarily providing many comments to others.

Relationships among Learner Characteristics, Peer Interactions, and Learning outcome Using Path Analysis

The results of path analysis (table 2) indicate that first, variables of learner characteristics affecting high in-degree centrality were intra-personal intelligence (β = .396) and verbal-linguistic intelligence (β = .235) more than prior knowledge and interpersonal intelligence. Conversely, variables of learner characteristics affecting interactions of high out-degree centrality were interpersonal intelligence (β = .286) and prior knowledge (β = .230) more than verbal-linguistic and intra-personal intelligence.

Table 2. Path coefficients among variables (n = 24)

Independent Variables	Dependent Variables			
	In-degree		Out-degree	
	Peer interactions	Learning outcome	Peer interactions	Learning outcome
prior knowledge	-.111	.367	.230	.301
verbal-linguistic intelligence	.235	.189	-.019	.220
interpersonal intelligence	-.263	-.093	.286	-.189
intra-personal intelligence	.396	-.099	-.083	-.034
peer interactions		.115		.232

Second, prior knowledge (β = .367(in-degree), β = .301(out-degree)) and verbal-linguistic intelligence (β = .189(in-degree), β = .220(out-degree)) among learner characteristics were related to learning outcome when in-degree and out-degree centrality mediated. Finally, the path coefficients for in-degree and out-degree interaction direct effect on learning outcome were .115(in-degree) and .232(out-degree). The effect on learning outcome of out-degree interaction was higher than that of in-degree interaction.

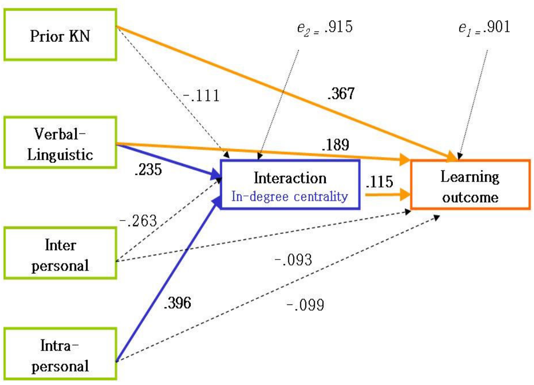

Figure 5: Path analysis of learning outcome intervened by in-degree centrality

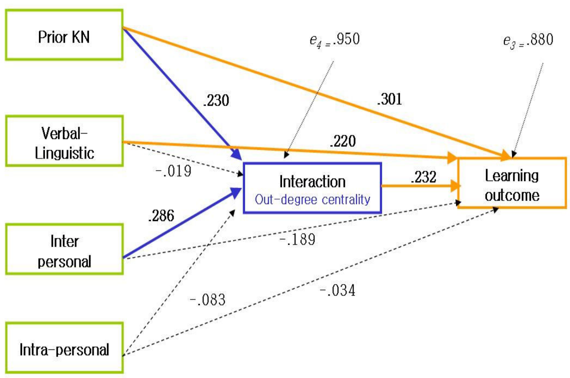

Figure 6: Path analysis of learning outcome intervened by out-degree centrality

⟶ positive effect - - ➜ negative effect e_1/e_3 : error to learning outcome e_2/e_4 : error to peer interaction

CONCLUSIONS

There are two conclusions. First, students with high intra-personal and verbal-linguistic intelligence were related to high in-degree centrality, while students with high interpersonal intelligence and prior knowledge were related to high out-degree centrality. In other words, "self smart" and "word smart" students were reflectors and good communicators in the learning process. These students were popular and played knowledge broker's roles in their community. On the other hand, "social smart" students and "high prior knowledge" students were open and friendly activators and delivered vast information in the learning community (Rovai, 2003).

Second, prior knowledge and verbal-linguistic intelligence among learner characteristics were related to learning outcome. Also, higher peer interactions were related to better learning outcome. These results indicated that peer interactions were important intervening variables that enhanced learning effects beyond the functional role of communication in community-based learning. Furthermore, higher peer interaction in an online learning community, as a knowledge network, may affect intangible outputs such as cohesiveness, trust, and sense of community as well as tangible outputs such as learning achievement and problem solving (Wen, 1998).

A limitation of this study was that the sample size was very small, reducing verification of the study. Twenty-four middle school students took part in the study. Thus it is required to obtain a larger sample size in extended period of time for future research. In addition, this study is needed to use not only quantitative analysis such as social network analysis but also qualitative methods such as interviews, questionnaires and message analysis for analyzing in-depth learner interaction patterns.

The implications of this study include that degree centrality of SNA is able to used as a measuring method for analyzing peer interactions in collaborative learning activities. Moreover, the result of relationships of peer interactions with learner characteristics and learning outcome may provide guidelines for developing learner model and collaborative supported mentoring agents in CSCL.

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