# Comparing Social Network Analysis of Posts with Counting of Posts as a Measurement of Learners' Participation in Facebook Discussions

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**ABSTRACT**
With the currently growing interest in social network services, many college courses use social network services as platforms for discussions, and a number of studies have been conducted on the use of social network analysis to measure students' participation in online discussions. This study aims to demonstrate the difference between counting posts and social network analysis of posts as a form of learners' participation in online discussions. To accomplish the goal, the study analyzed students' participation in Facebook discussions using the two methods and compared their results with those of MANOVAs. The between-group difference was significant when participation was measured by closeness centrality, but it was not significant when participation was measured by the number of posts. Although whether participation was measured by closeness centrality or by the number of posts did not make a significant difference in terms of learners' self-regulated learning level, the observed power of the closeness centrality measurement was higher than that of the number of posts measurement. These findings imply that it is important for a relational analysis to consider participation in terms of, not only the interaction between actors, but also closeness centrality, by comparing the two measurement methods.
**Keywords**: Social network analysis, closeness centrality, social media, participation, online discussion

## INTRODUCTION

There is a growing interest in social network services (SNSs), and accordingly, many college courses use SNSs as platforms for discussion. A number of studies have used social network analysis (SNA) to measure students' participation in online discussions (De Laat, Lally, Lipponen, & Simons, 2007; Lipponen, Rahikainen, Lallimo, & Hakkarainen, 2001; Lipponen, Rahikajnen, Hakkarainen, & Palonen, 2003; Stakias, Psoras, & Glykas, 2013; Tomsic, & Suthers, 2006). SNA aims to describe structural patterns of relationships among social actors, groups, and organizations and their implications (Hatala, 2006; Mitchell, 1969; Reffay & Chanier, 2003; Scott, 2013; Wasserman & Faust, 1995). It is an effective means for collecting, storing, and managing big data and analyzing and facilitating data visualization, which explains the relationship of exponential information (Sternitzke, Bartkowski, & Schramm, 2008; Suh & Shin, 2012). A number of previous studies have considered SNA to be a theory or analytic technique, or an interdisciplinary methodology for identifying social structural variables and properties. And Hoff, Raftery and Handcock (2002) said that SNA can demonstrate the relationships among interactive actors in an unobserved social space and provide more information such as actor's power, prestige and information authority in networks, which makes it a sophisticated statistical and useful research tool (Aviv, Erlich, Ravid, & Geva, 2003; Garton, Haythornwaite, & Wellman, 1997; Martinez, Dimitriadis, Rubia, Gomez, Garrachon, & Marcos, 2002; Wasserman & Faust, 1995).

As the importance about online discussion environment as new platforms for discussion has become more and more, there has been much empirical evidence of the usefulness of SNA methods for analyzing online networks, specifically, e-learning social awareness as well as evaluation technique in collaborative e-learning (Lambropoulos, Faulkner, & Culwin, 2012), the response relations among participants in asynchronous online discussions (Aviv et al, , 2003), and the participation in online-learning (Kim & Park, 2009; Park & Choi, 2011; Suh & Shin, 2012). Specifically, learner's participation- one of the factors predicting learners' achievements-, expressed as posts and/or comments in online discussion environment was influenced by learner's interactions (Moore & Marra, 2005; Jung, Choi, Lim, & Leem, 2002). So SNA method which is tools considering actors' interactions (including direct and indirect connections) can make it easy to comprehend the influence of each actor in networks. In this regard, it is highly possible that using SNA indexes can lead to conclude unprecedented implications which could not be revealed by using a simple count of meaningful posts because of SNA indexes demonstrating interactive relations between actors. Consequently, this study aims to demonstrate the difference between counting meaningful posts and SNA of posts as a form of learners' participation in online discussions by using the closeness centrality of posts to analyze authentic relations, interactions, and the position of actors.

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Most research reported that SNA indexes(especially closeness centrality) are able to analyze and enhance the deeper understanding of research based on interaction, however, how deep and wide in the research is not definite. Therefore, research to identify the difference between traditional research method and SNA method are required, and the research question is, "Are counting of meaningful posts and SNA of posts as a form of learners' participation different in the analysis of online discussions?"

## LITERATURE REVIEW

### Social Network Analysis

SNA, a strategy for investigating social networks or relations, can be applied in many fields as a new approach (Borgatti, Mehra, Brass, & Labianca, 2009; Otte & Rousseau, 2002; Stakias et al., 2013; Wasserman & Galaskiewicz, 1994). Some researchers have examined SNA from various aspects, including theories, methods, software, and the research paradigm, from an alternative metaphor to an analytic approach (Scott & Carrington, 2011; Stakias et al, 2013), while others have perceived it as a methodology. Whereas research in past decades focused on theoretical assumptions, recent studies have regarded SNA as a research methodology for systematically analyzing complex social-structure properties originating from the interdependence underlying function of social relations among analytic objects (Galaskiewicz & Wasserman, 1993; Makagon, McCowan, & Mench, 2012; Perna, Marra, & Napolitano, 2008; Shim & Lee, 2008; Wasserman & Faust, 1995). By focusing on relationships among actors rather than on each actor, SNA can analyze an organizational topological structure and its diffusion progress (Scott, 2013; Wasserman & Faust, 1995). In other words, it can provide an understanding of the network's features through link patterns, the number of links, and the structural concentration, not with attribute variables, but with relational variables. Also, visualization with an informal or formal network structure is useful for people who conduct research on big data (Perna et al., 2008). Considering the environments, it is necessary to deal with both the numeric comparison and the visualization of data.

The elements of analysis include connection, centrality, cohesion, and equivalence. Researchers mainly use density of connection and centrality as analytic techniques (Abbasi, Hossain, Uddin, & Rasmussen, 2011; Enriquez, 2008; Hamulic & Bijedic, 2009; Hawe & Ghali, 2008; Rice, Tulbert, Cederbaum, Adhikari, & Milburn, 2012). A node's connection is the number of neighboring nodes; it is the primary index that describes the node's characteristic in the network. It is possible to analyze a connection using concepts such as degree, density, reciprocity, and shortest path, to analyze the fundamental relationships with nodes and links. SNA focuses on relational attributes and considers in-degree and out-degree. The number of in-degrees is the number of lines directed toward the node, and the number of out-degrees is the number of lines directed to other points. According to graph theory, an in-degree is placed in the column of a matrix, whereas an out-degree is placed in the row. Centrality is used to measure the basis of a degree (Scott, 2013), the structure of which depends on certain criteria not based on the median or a node attached to many links. The aim of centrality structure analysis is to identify one of the most important nodes in a network and to investigate critical nodes for determining the degree of centralization. The components of centrality include degree centrality, closeness centrality, and betweenness centrality. Generally, the shorter the distance to other nodes is, the higher the closeness centrality is. In addition, closeness centrality indicates multiplicative inverse proportionality to distance to other nodes. The concept of a high level of closeness centrality is applied to all other nearby actors, indicating easy and rapid accessibility to other actors with minimum efforts (Wasserman & Faust, 1995).

### Participation in online discussion environment

Online environment as new platforms for discussion makes learners participate in discussion activity more and has a positive effect on high academic achievements, retention and transfer of learning. Besides, online discussion is beneficial for learners in that the learning environment is not influenced by time and location unlike traditional learning method. Therefore, previous studies (Berge, 1996; Dennen, 2001; Johnson & Johnson, 2000; Yellen, Winniford, & Sanford, 1995) suggested structure of groups, characteristics of learners, the role of tutor (or instructor) and strategies promoting discussion learning affect learner's participation in online discussion environment since that participation is closely associated with academic achievements. These research have been studied by quantitative and/or qualitative method, and also SNA indexes (Aviv et al, 2003; Lambropoulos et al, 2012; Moore & Marra, 2005; Jung et al, 2002).

Above all, since closeness centrality is measured by direct and indirect links among nodes found in an efficient organization (Shim & Lee, 2008), there have been a number of previous studies on the closeness centrality of participation in the online environment. Suh and Shin (2012) used closeness centrality providing a standardized value and a quantitative indication of concentration in online discussion activity, whose participation is an index that enables a multidimensional understanding of participation in learning as well as an analysis of interactions that take place among learners. Kim and Park (2009) used centrality of interaction on a Web bulletin board in order to analyze interdependency among learners in the Web environment. Interaction on a Web bulletin board is represented by the instructor's feedback, and its centrality is an index that affects learning, which facilitates the assessment of interactions as well as with whom learners are exchanging opinions and whose opinions are influential. Park and Choi (2011) viewed centrality in the number of posts as representing the level of participation and argued that analyzing the relational attributes of the discussion environment, such as the relationships among central and surrounding individuals, can be helpful toward understanding learners' characteristics. Therefore, it is necessary to combine conventional statistical research methodology with SNA or content analysis in order to identify new findings with profound implications and to broaden the context of analysis (Park & Choi, 2011) and allows a better understanding of the evolution process in online communities (Bae, Seo, & Baek, 2010). Among social network indices, the centrality of participation also has a significant effect on quantitative achievements (Cheong & Corbitt, 2009; Cho, Gay, Davidson, & Ingraffea, 2007; Russo & Koesten, 2005), providing a perspective of actual relationships and interactions rather than quantified numerical data.

## METHOD

### Participants and Treatment

To illustrate the approach, this paper analyzes the data drawn from a previous study that examined the effects of learners' self-regulated learning (SRL) skills and the instructor's feedback on learners' achievement and participation in Facebook discussions (Park & Lee, 2013). The experiment was implemented in two classes, which were taught by the same instructor with the same contents. One class was a control group not provided with instructor feedback, and the other class was an experimental group that was provided with instructor feedback. Then, based on the measured levels of all the participants' SRL, each class was divided into two groups representing high and low SRL, respectively. Thus, the participants were assigned to four groups: (1) feedback–high SRL, (2) feedback–low SRL, (3) non feedback–high SRL, and (4) non feedback–low SRL. The study analyzed the data of 108 participants who completed a self-regulation survey and posted meaningful posts.

### Measurement Instruments and Procedure

In the study, the learners' levels of SRL skills and achievement were drawn from Park and Lee's (2013) data. However, their participation level was newly measured. The number of meaningful posts was determined by the meaning unit technique, which was widely used in the message analysis. "Meaning unit," as the unit of analysis, is a unit of idea extracted from contents and contains a single item (Budd & Donohue, 1967). After dividing the data into units of analysis, the researchers measured the number of posts, excluding the number of extraneous posts related to contents. Together, they analyzed the meaning units to achieve reliability. When there were differences in opinion, the researchers discussed the analysis and made adjustments where necessary.
The researchers analyzed the participants' meaningful posts regardless of their length. Also, out-closeness centrality was calculated by the length of shortest paths that a specific actor posted meaningful posts to other actors. To measure out-closeness centrality, the meaningful posts' matrix of between participants was figured out at out-closeness centrality vector using NetMiner 3.0.

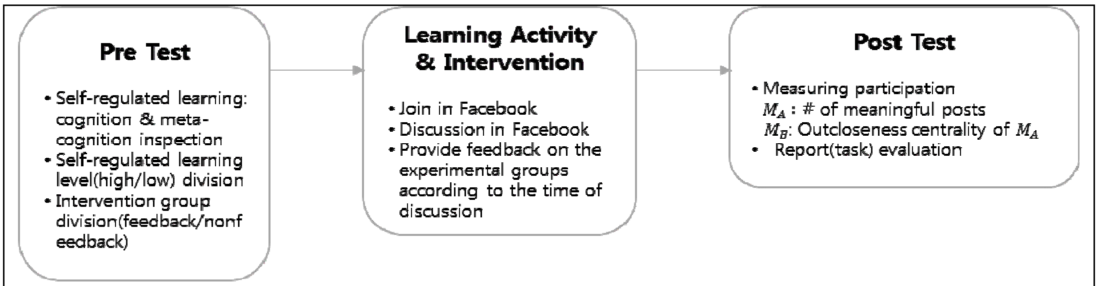


**Figure 1**: Revised from Park and Lee (2013). The Effects of Learners' Self-regulated Learning Skills and Instructor's Feedback on the Learners' Achievement and Participation in Facebook®-based Discussion of a Higher Education Setting. *The Journal of Educational Information and Media, 91*(2), 229–251.

### Analysis

To investigate the difference between SNA of posts and counting of meaningful posts, data were analyzed using NetMiner 3.0 and SPSS Statistics 18. For each measurement method that used feedback and level of self-regulation as independent variables with participation and achievement as dependent variables, descriptive statistics and multivariate analysis of variance were performed. The results of MANOVA depending on the measurement method were compared. For all statistical analyses, a level of significance of .05 was chosen.

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## RESULTS

### Result of counting and meaningful posts

Table 1 shows the descriptive statistics of the data regarding instructor feedback, learners' achievement according to level of SRL skills, logarithmic value of participation level, and number of cases. Measurement A is a semantic analysis of Park and Lee's data pertaining only to the meaningful comments on each post. The maximum level of achievement was set at 20, and the average level was 16.67.

**Table 1**: Descriptive Statistics of Measurement A

| Feedback | SRL | n | Measurement A (counting of meaningful posts) | | | | Achievement | |
|---|---|---|---|---|---|---|---|---|
| | | | Raw | | Log | | | |
| | | | M | SD | M | SD | M | SD |
| Feedback | High | 36 | 5.06 | 3.71 | 0.60 | 0.30 | 17.24 | 1.70 |
| | Low | 25 | 3.12 | 2.49 | 0.40 | 0.29 | 16.64 | 2.03 |
| | Sum | 61 | 4.26 | 3.38 | 0.52 | 0.31 | 16.99 | 1.85 |
| No Feedback | High | 21 | 6.38 | 5.29 | 0.66 | 0.38 | 16.96 | 1.96 |
| | Low | 26 | 4.08 | 2.26 | 0.55 | 0.25 | 15.65 | 1.56 |
| | Sum | 47 | 5.11 | 4.03 | 0.60 | 0.31 | 16.24 | 1.85 |
| **Sum** | | 108 | 4.63 | 3.69 | 055 | 0.31 | 16.67 | 1.88 |

MANOVA was conducted to determine if the instructor feedback and level of SRL skills had an effect on learners' achievement and participation. In Measurement A, the result of Levene's homogeneity of variance test indicated that the difference in covariance between two dependent variables–achievement (F = 1.201, p = .313) and the logarithmic value of participation (F = 1.992, p = .120)–was not statistically significant at the significance level of .05, satisfying MANOVA assumptions. Furthermore, Box's M test on the covariance matrices of the dependent variables yielded Box's M of 7.282 (F = .780, p = .635), passing the homogeneity test. The results of MANOVA are shown in Table 2.

**Table 2**: MANOVA results of Measurement A

| | | **Wilks's λ** | **F** | **P** | **NCP** | **Observed Power** |
|---|---|---|---|---|---|---|
| Measurement A (counting of meaningful posts) | Feedback | .922 | 4.330* | .016 | 8.661 | .740 |
| | SRL | .902 | 5.626* | .005 | 11.251 | .850 |
| | Feedback *SRL | .979 | 1.124 | .329 | 2.247 | .243 |

**p < .05*

### Result of the closeness centrality of posts

Table 3 shows the descriptive statistics of the data regarding instructor feedback, learners' achievement according to the level of SRL skills, average and standard deviation of the closeness centrality vector value, and number of cases. Measurement B is the closeness centrality of Measurement A's out-degree. Measurement B includes the interaction between actors, which is different from Measurement A, as well as the concept of closeness centrality based on the geodesic distances among actors.

Among the closeness centralities associated with participation, the out-closeness centrality vector value was used for Measurement B. In a network with directionality, closeness centrality that represents status and influence among actors in networks can be categorized into in-closeness centrality and out-closeness centrality. In-closeness centrality signifies the shortest distance from other actors to a specific actor, whereas out-closeness centrality is the shortest distance from a specific actor to others. In other words, closeness centrality is the shortest distance between actors, and in-closeness and out-closeness are categorized based on their direction. The data used in this study involved the number of posts left by each participant for other participants in an online environment, which is associated with out-closeness centrality directed from a specific actor to others. This is because learners' participation level in the online discussion environment was influenced by the instructor's feedback and other learners' direct and indirect effects; therefore, this study used out-closeness centrality, which provided a standardized value to analyze multidimensionally in detail in the online discussion activity. As a result, the out-closeness centrality vector value of the number of posts written by participants was used to

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indicate the level of participation in this study. The maximum level of achievement was identical with the scores used in the Measurement A analysis.

**Table 3**: Descriptive statistics of Measurement B

| Feedback | SRL | n | Measurement B (closeness centrality) | | | | | | Achievement | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | In-degree | | Out-degree | | Closeness centrality | | | |
| | | | M | SD | M | SD | M | SD | M | SD |
| Feedback | High | 36 | 4.14 | 2.99 | 4.06 | 3.71 | 0.34 | 0.15 | 17.24 | 1.70 |
| | Low | 25 | 2.24 | 1.79 | 2.12 | 2.49 | 0.15 | 0.13 | 16.64 | 2.03 |
| | Sum | 61 | 3.36 | 2.71 | 3.26 | 3.38 | 0.27 | 0.17 | 16.99 | 1.85 |
| No Feedback | High | 21 | 5.43 | 3.88 | 5.38 | 5.29 | 0.41 | 0.20 | 16.96 | 1.96 |
| | Low | 26 | 3.23 | 2.29 | 3.08 | 2.26 | 0.28 | 0.15 | 15.65 | 1.56 |
| | Sum | 47 | 4.21 | 3.26 | 4.11 | 4.03 | 0.34 | 0.18 | 16.24 | 1.85 |
| **Sum** | | 108 | 3.73 | 2.98 | 3.63 | 3.69 | 0.30 | 0.18 | 16.67 | 1.88 |

MANOVA was also conducted to determine if the instructor feedback and level of SRL skills had an effect on learners' achievement and participation. In Measurement B, the result of Levene's homogeneity of variance test indicated that the difference in covariance between two dependent variables—achievement ($F = 1.201$, $p = .313$) and the closeness centrality of participation ($F = .738$, $p = .532$)—was not statistically significant at the significance level of .05, satisfying the assumptions. Box's M test on the covariance matrices of the dependent variables yielded Box's M of 12.434 ($F = 1.331$, $p = .214$), passing the homogeneity test. The results of MANOVA are shown in Table 4.

**Table 4**: MANOVA results of Measurement B

| | | Wilks's λ | F | P | NCP | Observed Power |
|---|---|---|---|---|---|---|
| Measurement B (closeness centrality) | Feedback | .873 | 7.501* | .001 | 15.002 | .938 |
| | SRL | .776 | 14.895* | .000 | 29.790 | .999 |
| | Feedback *SRL | .975 | 1.346 | .265 | 2.692 | .285 |

*$p < .05$

**Comparison of closeness centrality with counting of meaningful posts**

Table 5 shows the comparison of two MANOVAs. There were statistical differences between Measurements A and B. First, MANOVA confirms that there was no significant difference in participation measured by the counting of meaningful posts (Measurement A) based on the provision of instructor feedback ($F = 3.086$, $p = .082$), but participation measured by closeness centrality (Measurement B) based on the provision of instructor feedback differed significantly ($F = 10.014$, $p = .002$). Second, Measurements A and B were significantly different in terms of participation based on learners' SRL level. However, the observed powers of Measurements A and B were .763 and .999, respectively.

**Table 5**: Comparison of univariate tests of closeness centrality with those of number of posts (n = 108)

| | | | Type III SS | df | MS | F | P | Partial $\eta^2$ | Observed Power |
|---|---|---|---|---|---|---|---|---|---|
| Measurement A (counting of meaningful posts) | Feedback | Achievement | 10.388 | 1 | 10.388 | 3.196 | .077 | .030 | .425 |
| | | Participation | .280 | 1 | .280 | 3.086 | .082 | .029 | .413 |
| | SRL | Achievement | 23.607 | 1 | 23.607 | 7.263* | .008 | .065 | .761 |
| | | Participation | .663 | 1 | .663 | 7.297* | .008 | .066 | .763 |
| | Feedback *SRL | Achievement | 3.349 | 1 | 3.349 | 1.030 | .312 | .010 | .171 |
| | | Participation | .056 | 1 | .056 | .611 | .436 | .006 | .121 |
| Measurement | Feedback | Achievement | 10.388 | 1 | 10.388 | 3.196 | .077 | .030 | .425 |

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| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| B (closeness centrality) | | Closeness centrality | .244 | 1 | .244 | 10.014* | .002 | .088 | .880 |
| | SRL | Achievement | 23.607 | 1 | 23.607 | 7.263* | .008 | .065 | .761 |
| | | Closeness centrality | .637 | 1 | .637 | 26.153* | .000 | .201 | .999 |
| | Feedback *SRL | Achievement | 3.349 | 1 | 3.349 | 1.030 | .312 | .010 | .171 |
| | | Closeness centrality | .032 | 1 | .032 | 1.300 | .257 | .012 | .204 |

*$p < .05$

In conclusion, it is important for relational analysis to consider participation in terms of, not only interaction between actors, but also closeness centrality, by comparing the two measurement methods. Because the closeness centrality of SNA focuses on relationships between actors instead of each individual actor and reflects social phenomena for analyzing the implications of relation, SNA should be widely applied in intra-organizational actors' positions as well as in inter-organizational network.

## DISCUSSION

The major goal of quantitative research focused on variables is to test a theory and offer a broad explanation about the prediction. However, a variety of factor-control variables, measuring variables, intervention variables, and moderating variables that affect the experimental environment are attribute variables, which only consider the direct connection between variables. Research focusing on attribute variables can provide a solution to a problem, but it is not an effective method that takes relational attributes into account. In accordance with the state of complex society and environment, it is necessary to comprehend unseen things and conduct sophisticated analysis. Therefore, this study examined the difference between SNA of posts and counting meaningful posts as forms of learners' participation in online discussion.

The results of this study can be summarized in three parts.
First, the participation measured by closeness centrality based on the provision of instructor's feedback was significant, but measured counting of meaningful posts was not significant. Since the closeness centrality is associated with relationship between an individual and other members of the network directly and unmediatedly (Cho et al, 2007), in this regard, the result indicated that instructor's feedback have a positive effect on other participants who is 'indirectly' connected with a participant in whole network space That is, SNA indexes are able to avoid failing to consider influence of instructor's feedback in online environment unlike numerical value by counting of meaningful posts, the conclusion is that instructor's feedback in online environment widely promotes learner's participation as a whole.

Second, both participation measured by closeness centrality of posts and participation by counting meaningful posts were significantly different based on the level of learners' SRL; and participation measured by closeness centrality of posts was more significantly than that by counting posts simply. In addition, a number of previous studies have used the closeness centrality of participation to gain a better understanding of numerous social networks in the online environment (Bae et al., 2010; Suh & Shin, 2012; Park & Choi, 2011; Rice Doran, Doran, & Mazur, 2011). The level of learners' participation can vary according to diverse factors, such as gender, background, cultural traits, prior training and education, and prior experience (Gay & Howard, 2001), and the same can be said about the online learning environment (Wang, 2007). Taking these factors into account, Rice Doran et al (2011) suggested that SNA should be used to analyze the potential pattern of participation in the online learning environment. In conclusion, Rice Doran et al (2011) argued that when analyzing learners' participation in an online discussion and learning environment, researchers should take various potential elements into account by using the closeness centrality of the number of posts rather than simply looking at the number of posts, which is consistent with the results of this study.

Third, the difference between participation measured by closeness centrality and counting of meaningful posts was the observed power. According to Tables 2, 4, and 5, each MANOVA result and univariate test about feedback and SRL were statistically significant, but the observed power of the closeness centrality measurement was higher than that of the counting of meaningful posts measurement. This means that higher observed power implied lower type II error. In this way, SNA of posts is a credible and valid method compared with the general counting of meaningful posts, especially for the analysis of a complex and dimensional learning environment influenced by various factors.

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Overall, these findings indicate that SNA measures can explain networked relationships more specifically in an online learning environment. Although counting meaningful posts can be used to analyze learners' participation in an online learning environment, it is more important how much each actor plays a central and critical role in online discussions. Given the traits of the online learning environment, analysis of the central role in the environment can be verified by SNA measures, namely regarding the counting of meaningful posts, as learners' participation does not include attributes of the online learning environment; however, SNA measures that consider various factors not overlooked can involve the traits of the online learning situation.

Going forward given the diversity, complexity, and massive scale of big data, network visualization will facilitate data analysis. This can also be useful in analyzing data stored in the Learning Management System (LMS), which includes nonstructural and large-scale data, such as the learning activity status, posts left by learners, log-on times, study duration, and participation in team projects. For example, in Moodle-based LMS, the instructor may use display replies in unthreaded form for SNA. Therefore, in analyzing the LMS environment with accumulated big data, it is necessary to use visualized images of the network in addition to the basic statistics data. Through this, the network's structure and characteristics in online discussions can be better understood.

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