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Harnessing Sociographs to Design Discussion Groups for Mathematics Learning: A Social Network Analysis Approach

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***Abstract* – As one of the 21st-century competencies, mathematical communication ability must be achieved through interactions created between teachers and students, and among students. Discussion groups are an alternative that generates interaction between students. Currently, not many teachers design discussion groups based on communication networks. This study aims to describe the results of Social Networking Analysis in independent mathematics learning through group discussions using graph representation. This network analysis is a complete communication network analysis with a quantitative descriptive method using UCINET Ver.6. This study uses five aspects to analyze the data, namely: (1) eigenvector centrality, (2) degree centrality, (3) closeness centrality, (4) betweenness centrality, and (5) network density. The subjects of this study were 32 students at a junior high school in Yogyakarta, Indonesia, who were selected based on suggestions from the mathematics teacher.**

The data in this study were collected using questionnaires, observation, and interviews. Hence, the validity and reliability of each one has been examined. According to the study, 43.8% of students' independent arithmetic learning falls into the medium category. It implies that students frequently decide on study sessions with discussion partners and take the initiative to identify and arrange the answers. Based on the data, four groups were created, each with eight pupils. This study is anticipated to serve as a benchmark for other investigations into the efficacy of discussion groups created in conformity with 21st-century skills.

***Keywords* – Sociograph, social networking analysis, mathematics learning.**

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1. Introduction

The four 21st-century competencies that students must have are communication, collaboration, critical thinking, and creativity [1], [2], [3], [4], [5], [6]. Communication skills are the ability to express ideas and describe and discuss mathematical concepts coherently and clearly (oral or written) [7]. Challenging students to communicate and interact both orally and written in learning mathematics can construct and deepen their conceptual understanding [7], and everything that affects learning can be maximized through interaction and communication [8], [9]. Interaction in the learning process is between students and teachers and between students and students [10]. The interaction among students allows them to exchange information and ideas in group projects, group discussions, and case studies, and it can stimulate collaboration and sharing of knowledge and skills in mathematics learning [11]. For students to have communication skills (as one of the mathematical abilities), interaction is needed in a discussion group that can stimulate collaboration and sharing of knowledge and skills.

Interaction in a discussion group is necessary because the communication network that is formed is beneficial for the process of forming student character and supports students' skills in thinking and solving problems [12], [13], [14].

Group discussions without a communication network between students make learning not optimal because there is awkwardness and discomfort [15], [16]. This makes it difficult for students to express their thoughts, thus not allowing interaction between them [17].

Based on observations and interviews with teachers at a school in Yogyakarta, Indonesia, it was found that teachers were more dominant in designing discussion groups by looking at seats and attendance lists, moreover, without looking at the communication network between students. Consequently, one of the discussion groups was passive characterized by lowered and often silent interactions. While it's not the case for all discussion groups, addressing the issue of passivity is crucial, as it has the potential to negatively impact students' capabilities. Therefore, it is necessary to analyze the communication network in designing a group discussion to optimize mathematics learning and positively impact students' mathematical communication skills.

2. Methodology

This quantitative descriptive research aims to describe the results of student communication network analysis (Social Networking Analysis) in independent mathematics learning through group discussions using graph representation, where each vertex (node) states a relationship. The observation of sociometric data is to clarify the representation of independent learning that has been designed. This sociometric research data shows which friends are the most liked in the discussion and who are not liked. This is a complete communication network analysis with a quantitative descriptive method. [18] using NetDraw-assisted UCINET Ver.6. The results of this analysis are the values of 5 aspects, namely: (1) eigenvector centrality, (2) degree centrality, (3) closeness centrality, (4) betweenness centrality, and (5) network density [19].

The subjects of this study were 32 class VIII students at a junior high school in Yogyakarta, Indonesia, who were selected based on suggestions from the mathematics teacher (i.e., with a class with students of various characters). The object of this research is a self-learning communication network through group discussions during mathematics learning. The data in this study were collected using questionnaires, observation, and interviews. The instruments in this study were self-learning questionnaires, sociometric questionnaires, student communication and network observation sheets, and interview guidelines, all of which have been tested for validity and reliability.

The data analysis steps in this study include: (1) testing the validity and reliability of the instrument; (2) data triangulation; (3) data presentation; and (4) analysis of research data [20], [21], [22].

3. Results and Discussion

The data in this study are self-learning questionnaire scores, sociometric questionnaire scores, descriptions of observations, and interview scripts. Before discussing related data, the subjects in this study will be shown, as seen in Table 1.

Table 1. The subjects of the study

No	Subject	Gender	No	Subject	Gender
1	AR	Male	17	FA	Male
2	AS	Female	18	SA	Female
3	FS	Male	19	BA	Male
4	FT	Female	20	SN	Female
5	HA	Male	21	ZA	Male
6	IS	Female	22	IN	Female
7	KH	Female	23	AY	Female
8	MF	Female	24	SE	Female
9	NI	Female	25	SY	Male
10	NO	Male	26	BO	Male
11	NU	Female	27	AN	Female
12	OK	Female	28	MU	Male
13	QU	Female	29	FD	Male
14	RO	Male	30	FJ	Male
15	SI	Female	31	EV	Female
16	ST	Female	32	NR	Female

Self-learning questionnaires and sociometric questionnaires were given to 30 students listed in Table 1. The self-learning questionnaire data and analysis of results can be seen in Table 2.

Table 2. The level of student self-learning (group discussion) in class

Validity	Category	Frequency	Valid Percent
Valid	Very low	3	9.4
	Low	7	21.9
	Enough	14	43.8
	High	6	18.8
	Very high	2	6.3
	Total	32	100.0

Table 2 shows that the highest frequency is in the "Enough" category of 14, with a valid percentage of 43.8%. This shows that students tend to choose and determine study time with discussion partners and become in control of finding and organizing answers, meaning the teacher must control the learning process.

Sociometric questionnaire data, observations, and interviews are inputted into Ucinet and represented through a sociograph that describes the relationship between subjects in independent learning in class.

A sociograph or sociometry analysis is used to find out the communication network in the student's independent learning process, which is a form of research findings from the effects of socio-mathematical norms [23]. The interaction and representation of the self-learning communication network with the sociograph is a visualization of student relationships with each line showing the relationships between students, whether they interact with each other or not.

In sociograph analysis, points in an image called 'nodes' represent individuals or actors connected by lines, namely 'vertex'. Two nodes are said to be connected if there is a line that connects them or forms a relationship between actors called a 'link'. Nodes, vertices, and links have their meanings defined by measure of the communication network. The size of the communication network is (1) network density; (2) eigenvector centrality; (3) degree centrality; (4) closeness centrality; and (5) betweenness centrality [24], [25], [26].

The results of the representation of independent learning communication networks with a sociograph can be seen in Figure 1.

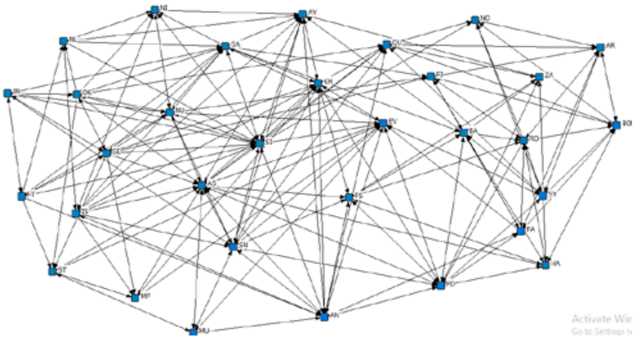

Figure 1. Communication network representation with a sociograph

In Figure 1, it can be seen that AS and SI have the most vertex, which means they have the most networks with other students. In addition to the representation shown in Figure 1, there are also the results of the analysis of communication networks in Ucinet, including density, degree centrality, eigenvector centrality, closeness centrality, and betweenness centrality.

Density aims to measure the number of connections made by each actor in a network so that it is possible to see the strength of the relationships that might occur in the entire network [18], [21]. The relationship between actors in a communication network is strong if more than 30% [27], [28], [29], [30].

The density in the Unicet application is 0.2657 or 26.57%, with a standard deviation of 0.4417. It implies that the connections within the communication network among actors in independent learning are not particularly strong.

The interaction between students in the self-learning communication network has been somewhat limited or minimal. The results of the self-learning questionnaire analysis, which is categorized as enough and the density value is still low, show that independent learning is less effective in generating interactions in the stability of the communication network. Therefore, it is necessary to carry out further analysis related to the independent learning communication network so that it is possible to form new discussion groups to increase the intensity of student communication.

Eigenvector centrality aims to find the most central actor in the social network [31]. An actor with a high eigenvector will be in the middle of the network. The higher the eigenvector value, the more critical the actor's position is in connecting each actor in the communication network [18], [21], [31]. Based on the Eigenvector centrality analysis, the actor with the highest eigenvector value is obtained, as shown in Table 3.

Table 3. Eigenvector centrality analysis results

Subject	Eigenvec	nEigenvec
SI	0.309	43.682
AS	0.304	43.030
KH	0.265	37.480
SN	0.256	36.261
AN	0.248	35.130
EV	0.239	33.764
SA	0.238	33.687
…	…	…

Table 3 shows that SI has the highest eigenvector value, which is 0.309, and has the highest eigenvector, which is 45.957. IS is a central actor with a vital role in connecting every actor in the communication network.

Degree centrality aims to measure the role of an actor in the network. An actor marks the depiction in the diagram with many connecting lines (vertex). An actor with a high degree of centrality is an actor who has many contacts with other actors, which means the actor is famous in the network [21], [32]. Five actors with the highest degree centrality values were obtained based on the degree centrality analysis, as seen in Table 4.

Table 4. Degree centrality analysis results

Subject	In Degree	Out Degree	nrmIn Degree	nrmOutDegree
SA	13.000	11.000	41.935	35.484
AS	13.000	16.000	41.935	51.613
AN	12.000	11.000	38.710	35.484
KH	12.000	10.000	38.710	32.258
SN	12.000	9.000	38.710	29.032
…	…	…	…	…

The five actors in Table 4 have the highest degree of centrality compared to other actors in the communication network, so they can easily discuss with anyone in class because of their popularity. In addition, the average degree centrality is 8.219, indicating that each actor will interact with at least eight actors in the communication network. Based on this, the discussion groups to be designed must contain a maximum of 8 actors in each group so that effective interaction occurs between students.

Closeness centrality is the average distance a node requires to reach all nodes in the network, so this measure describes the closeness between nodes and the vital role of nodes in the network [33], [34]. The smaller the node distance, the tighter the communication network is, so actors with high closeness centrality will spread information faster and more expensive to all actors [19]. Based on the closeness centrality analysis of independent learning classes, five actors with the highest closeness centrality values are obtained, which can be seen in Table 5.

Table 5. Closeness centrality analysis results

Subject	In Farness	Out Farness	In Closeness	Out Closeness
AS	49.000	51.000	63.265	60.784
QU	51.000	79.000	60.784	39.241
SI	52.000	51.000	59.615	60.784
EV	52.000	54.000	59.615	57.407
FD	53.000	58.000	58.491	53.448
…	…	…	…	…

The five actors in Table 5 are the easiest to contact when discussing because they are fast and broad in discussion to transfer knowledge and information without many intermediaries.

Betweenness centrality is a measurement to determine how far a node can control the flow of information between other actors and how well actors can facilitate communication with other actors [19], [35]. Actors with high betweenness centrality have an enormous capacity to facilitate interactions between actors. Based on the betweenness centrality analysis, five actors have the highest betweenness centrality values, which can be seen in Table 6.

Table 6. Betweenness centrality analysis results

Subject	Betweenness	In Betweenness
AS	97.912	10.528
SI	97.053	10.436
EV	80.312	8.636
FJ	77.166	8.297
SA	76.038	8.176
…	…	…

The actor with the highest betweenness centrality in Table 6 will become a dependent actor for other actors as a bridge for all discussion groups and a source of discussion for actors to control information.

Based on the analysis, discussion groups are designed for mathematics learning, which can strengthen interactions between students so that learning is more optimal [36]. Therefore, in each designed group, an actor must have the highest degree of centrality, eigenvector centrality, closeness centrality, and betweenness centrality results. At the same time, the actors who have low results are distributed in each group so that the quality of its members can be balanced in one group.

Referring to the results of degree centrality, the number of students per group is eight people, so the number of groups is four groups. The four groups can be seen in Table 7.

Table 7. Discussion groups based on social network analysis

Group 1	Group 2	Group 3	Group 4
AS	SI	SA	EV
KH	NU	AY	AN
MF	FT	SE	SN
IS	NI	IN	SY
ST	OK	NR	MU
FS	QU	BA	FD
RO	NO	FJ	BO
HA	AR	ZA	FA

In addition, the design of this discussion group is also presented on the sociograph with different color nodes. The sociograph can be seen in Figure 2.

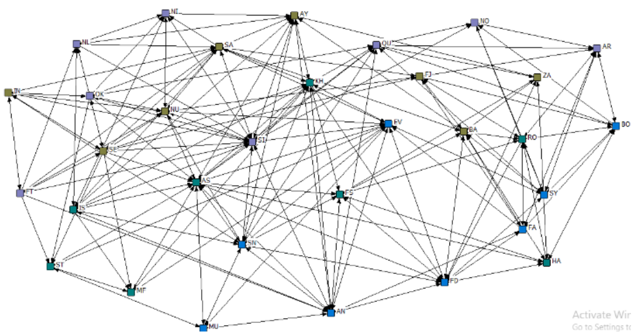

Figure 2. Sosiograph of discussion groups with color nodes

Group 1, there is AS, the center of the network, because it has an eigenvector of 43.030, degree centrality of 41.935, closeness centrality of 63.265, and betweenness centrality of 10.520, the highest value compared to group members. In other words, AS is an essential factor because it is the center of the communication network in the group, has many relationships with other actors in the network (popular), and is easy and fast in disseminating information [18], [21], [23], [36].

Apart from the AS, there are KH with relatively high values of eigenvector, degree centrality, closeness centrality, and betweenness centrality, so they become actors with an essential role in supporting the AS. Judging from the sociograph in Figure 2, KH is an actor with vertexes connected quite a lot with near and far nodes. This means that KH has many relationships with both close and far nodes. Through KH, Group 1 found it easier to obtain and disseminate information. However, in Group 1, there are also MF and ST, which have low eigenvector values, degree centrality, closeness centrality, and betweenness centrality. This will be a manageable problem because other actors, such as AS and KH, can build communication between group one and connect MF and ST with other actors in the network. In addition, IS, ST, FS, RO, and HA actors have high closeness centrality so that they can become intermediaries and connectors for transferring knowledge in Group 1.

In group 2, the total value of degree centrality was 196.755, eigenvector centrality was 170.211, closeness centrality was 390.225, and relationship centrality was 17.978. The primary network in this group is SI because it obtains high network values, namely, an eigenvector of 43.682, degree centrality of 38.710, closeness centrality of 59.615, and betweenness centrality of 10.436. In addition, the results of the sociometric questionnaire show that SI is the actor most other students communicate through. Other actors supporting the process of running independent learning in this group to run optimally are QU, OK, and FT. QU is an actor with a closeness score of 60.784, so QU has a very close relationship with other actors. The results of observations during the independent learning process show that QU can lighten the mood during discussions with high communication intensity [37].

OK obtained an eigenvector centrality value of 23.978, so that it played a role in assisting SI in leading the course of independent learning discussions. Meanwhile, FT has a good degree centrality value of 25.806, which means FT is quite popular. The popularity of FT can be used by Group 2 to build more relationships with other groups. On the other hand, members of Group 2 who do not have high centralities, such as NI, NO, AR, and NU, also have an essential role. For example, AR has the highest closeness centrality compared to other actors in its group, namely 60.784. This means that AR can disseminate information or knowledge more widely and quickly even though AR has low credibility. This is not a problem because other actors, such as IS, can make up for this deficiency.

In Group 3, SA is a network center with an eigenvector value of 33.687, degree centrality of 41.935, closeness centrality of 56.364, and betweenness centrality of 8.176.

SA has the highest degree of centrality value among other actors in group 3, meaning that SA is the most famous actor among other actors [19], [21]. SA also has many close relationships inside and outside the group members 3. Other actors with high centrality results to help SA are AY, SE, and FJ, with high enough centrality values to support SA in building communication networks and strengthening the relationships in the group. The advantage is that the group becomes solid and more compact [38]. Other members in Group 3, namely IN, NR, BA, and ZA, have average centrality results. Even though the value of centrality is not high, these members have an essential role in balancing the communication network within the group so that no one is dominant.

In group 4, EV is the major network chosen based on the results of the sociometric questionnaire and high centrality values. As the centrality of the EV network, AN is highly supported because both have a high degree of centrality and eigenvector centrality. EV eigenvector centrality value is 33.687; degree centrality is 41.935; closeness centrality is 56.364; and betweenness centrality is 8.176. In comparison, AN has an eigenvector centrality value of 35.130, degree centrality of 38.710, closeness centrality of 58.491, and betweenness centrality of 5.361. Judging from the centrality results, AN has a vital position in the communication network, especially in supporting EV as a network center. Apart from EV, AN, SN, FD, and SY, actors have high centrality values. SN has an eigenvector value of 36.261 and a degree of centrality of 38.710. The FD centrality closeness value of 58.491 is in the high category, indicating that the FD actor unites other actors in one group so that they are compact. SY has an average centrality value, but the betweenness centrality SY value is relatively high 4.866. SY can assist EV and AN in controlling the information in this group. Members of other groups, namely MU, BO, and FA, were chosen because they are actors who have a good or close relationship or communication with members of this group, so even though their centrality score is not too high, with them, this group will be balanced and have equal ability.

Designing discussion groups based on communication network analysis is expected to maximize interaction between students so that independent mathematics learning through group discussions can be carried out optimally and improve students' mathematical communication. Mastery of students in developing their mathematical communication skills has indirectly instilled four 21st-century competencies in the students themselves.

4. Conclusion

Learning mathematics independently in class VIII of a junior high school in Yogyakarta, Indonesia, is in the medium category with a percentage of 43.8%. This shows that students tend to choose and determine study time with discussion partners and become in control of finding and organizing answers, meaning the teacher needs to completely control the learning process. The density value in the self-learning communication network is 0.2657, which indicates that the relationship in the network is not very strong, so each student is not necessarily related to every student in the class. It is necessary to design discussion groups by looking at the results of sociograph analysis with Ucinet to support independent learning in the classroom. They have, moreover, obtained four groups, with each group consisting of 8 students. This research is expected to be a reference in further research regarding the effectiveness of discussion groups designed for 21st-century competencies.

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