Analysis of Scholarly Communications of Students on Twitter

https://doi.org/10.3991/ijet.v17i09.27197

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Abstract—As part of an applied activity of a university course in Japan, a total of 65 students posted messages on Twitter regarding world issues to expand the scope of scholarly communication with social users on Twitter. The students' motivation to learn was evaluated using a standard questionnaire. Gradually, social media analysis was introduced for examination from a holistic perspective. For the first time, we also attempted to use exponential random graph models to investigate the structures of a network with statistical evidences. The connections exhibited by students were classified into three types: crossing, private, and isolation. The multiple comparison test showed a significant result: students of the crossing type were more motivated than those of the isolation type. The result also showed how students communicate with users from other networks, elucidated the connections and structures of tweets, and extracted influential students from the network. In conclusion, the skills to connect with social Twitter users as well as communication among students were found to be indispensable factors in expanding the scholarly network and developing social capital in the community.

Keywords—ARCS, ERGMs, online connections, Twitter, university students

1 Introduction

Small groups, such as those in schools, workplaces, or neighborhoods, can communicate closely through social media due to their sense of belonging and shared social norms [1]. Such modes of communication among closely connected individuals has become largely routinized in everyday conversations [2]. However, interpersonal relationships that connect individuals who are members of different communities through the social network tend to be weaker. Granovetter [3] compares communities with varying acquaintance levels to find that 84% of people make important decisions to secure their jobs through information they see only "occasionally" or "rarely." This shows the benefits of communicating with individuals to whom we are weakly connected. Buchanan [4] also concludes that without weak ties, a network would be fragmented into many isolated cliques. Further, Burt [5] emphasizes the way different parts of networks are bridged, noting the spread of new ideas and opportunities through weak ties, and the informational benefits generated when weak ties help bridge structural gaps between communities. When weak ties develop into strong ones, it becomes possible to access scarce resources and information [6].

In fact, there are advantages of learning to access new resources on social media [7] and in the knowledge society which has complexity, interactivity, reflexivity, and interpretation characteristics [8]. Social media encourages participation and collective input [9]. Moreover, learning and performance are bonding characteristics of social capital, which is the aggregate of resources acquired from the social network [10]. However, as reported by Moore [11], many unwary start-up communities have fallen into the "chasm," that is, a situation wherein ties between uses of different communities are lacking. Thus, the research question arises as to how students' emerging scholarly communities can connect to other social communities.

To expand the scholarly student community, interdisciplinary research on the social capital theory reported the need for investment in personal relationships and social structures that facilitate the achievement of individual or collective goals [12].

1.1 Social media and motivation

For social capital to be converted into actual resources, users must have the motivation to build communication ties. This motivational factor was identified based on detailed reviews and investigations [12-15]. In other words, the social capital theory contends that the resources available through networks are effectively mobilized only when users have the willingness to engage in social action [16].

Regarding valuing motivation, the attributes of motivational concepts are analyzed, and Keller's four components of learner motivation are defined as the acronym ARCS—attention, relevance, confidence, and satisfaction [17]. In addition, Keller provides a standard questionnaire based on the ARCS model to measure students' motivation, called the Instructional Material Motivation Scale (IMMS). The IMMS also includes various measures of motivation for the information media environment [18, 19].

1.2 Research questions and aims

In this case study, we monitored university students' use of the social media platform, Twitter, to communicate with social media users to build connections based on scholarly content. While previous studies showed students reported difficulties in developing connections with other communities, this study challenged how students contrive to make connections and what changes emerge in their online network through analysis of extracted online data.

Here, the following research questions were posed:

a) Can students communicate with users from other networks?
b) What is the noticeable structure of the network?
c) How do tweets from students with higher levels of motivation behave in the network?
d) How could students expand their scholarly network?

This study framed the following aims to investigate these research questions:

a) Identify the difference between connections with classmates and connections with other social users.
b) Characterize the structure of the network when connections are made.
c) Describe the motivation levels of students by type and show the effects on communication with social users.
d) Identify the way to expand scholarly networks.

2 Materials and methods

A general education course was chosen as the target course, in which students at a Japanese university learn about world issues. A total of 65 first-year undergraduate students from three disciplines (literature, engineering, and nursing) were recruited over a period of six weeks from May to June 2020. The target university has a strategic approach toward internationalization and provides international education courses for students of all disciplines. The target course was an introductory class. The course comprised five content-related sections on major world issues (Table 1), with each section covering four subtopics relevant to a range of scholarly content areas and two related indicators (right column in Table 1). Students accessed successive data on indicators for their selected country (middle column in Table 1) from the World Bank database and other online resources.

Table 1. Content covered during the course

Session	Country	Keywords in subtopics, indicators
Economic situation	Emerging	GDP, GNI, unemployment rate, rate of living below the national poverty line
Poverty	Developing	Population below the international poverty line, rate of incidence of malaria, infant mortality rate, prevalence of undernourishment, rate of population access to electricity
Disparity	Developed	GNI index, employment rate in industry, total debt service (% of exports), enrolment rate in tertiary education, rate of individuals using the Internet
Urban problems	Any	Population in urban agglomerations, proportion of seats held by women in national parliaments, rate of intentional homicides, PM2.5 air pollution (µg/m3), rate of population living in slums
Water and Sanitation	Emerging	People using safely managed sanitation services, maternal mortality ratio, forest area, coverage of social safety net programs, total natural resource rents

Note. GDP: gross domestic product; GNI: gross national income; PM: atmospheric particulate matter.

The course used the communication-jigsaw group learning method [20], which is the applied version of the jigsaw method [21], to involve all the students in discussions on all subtopics. We put four members together for each jigsaw group. More specifically, each group member was allotted a different subtopic and asked to write short reports to explain changes observed in the data and relationships between indicators. They, then, exchanged their reports and discussed their opinions in a jigsaw group.

Subsequently, all the reports were uploaded on the message board of the university's Moodle e-Learning platform; students could, thus, exchange opinions with all their classmates and a lecturer. At the end of the classroom activities, the teacher delivered a reflective lecture to provide a deeper understanding of the topic. Each section was designed to offer detailed knowledge of related indicators and to provide an in-depth understanding of these topics.

After each session, all students were asked to tweet on Twitter about their personal opinions about the world issue they covered and to exchange views with other Twitter users. Students could share their opinions to find a relevant social Twitter user to exchange opinions within a discipline. They were allowed to tweet as many times as they wished.

Regarding media skills and online experience, all the students owned PCs and smartphones and used social media in their daily lives; they were netizens and digital natives.

The students could post isolated tweets, "replies" (i.e., tweets responding to a particular individual), "quote retweets" (i.e., forwarding another individual's original tweet), and "mentions" (i.e., tweets that contained someone's account name). They could also add hashtags for keywords or topics to enhance their visibility on Twitter. To identify the connections that emerged from the course, all the students were required to include the lesson hashtag in their tweets.

2.1 Data collection

The IMMS analysis was executed at the end of the course. It consists of the same four components as ARCS and includes 36 items measured on a five-point Likert scale, ranging from 1 (not true) to 5 (very true). The measure can be scored for each subscale and for the total scale. The scores range from 36 to 180, with a midpoint of 108 for the total scale.

To the best of our knowledge, this study is the first to implement the social network analysis (SNA) and exponential random graph models (ERGMs) to investigate the motivation and structures of scholarly connections on Twitter. Using Twitter in a university course allows for the exchange of viewpoints, collaboration, clarification, and communication about course content, and sharing of resources and experiences with the public [22]. All students in this study tweeted to communicate with their selected social media users on Twitter. In order to assess students' connections and their status in the Twitter network, the SNA was used. As part of the SNA, all the connections were initially converted to a node (a user) and an edge (a tweet). Twitter's application programming interface was used to access the communication data. NodeXL Pro, a toolkit for the SNA, was used to collect the data, calculate metrics, and generate social group graphs. For the statistical analysis, ERGMs were implemented in the "ergm package" contained in the "statnet" suite of network analysis packages in R (ver. 4.0.4; R Foundation). It is actively maintained and developed by network scientists at the University of Washington, among others [23]. The ERGMs predict the propensity that a pair of nodes and the structural features in a network will have a connection. An ERGM also identifies the probability of tie formation in the network, and this value ranges from 0 to 1.

2.2 Ethical Considerations

All students created new accounts on Twitter using pseudonyms especially for this study. All our data are completely anonymized and were collected and distributed in accordance with Twitter's Developer Policy. Informed consent was obtained from all participating students. All students had the option to remain silent if they did not want to make a tweet public. During the course period, a teacher was continuously monitoring student activity on Twitter to ensure their online safety, and students had also previously completed cyber safety training. All procedures carried out in this work were in accordance with the ethical standards of the institutional and/or national research committee and complied with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

3 Results

The surveyed scholarly network had characteristics of an unbounded network that did not have set membership with an open invitation to anyone on Twitter. The data collected on tweets represented 197 users—65 students, 10 students who had withdrawn from the course, 10 students not in the course, and 112 social users on Twitter. We identified 767 tweets posted by 65 students. The mean of tweets by students was calculated (M = 11.8, SD = 4.15) and showed their active tweeting.

3.1 Emerging network

Table 2 shows the calculated metrics for the resulting network. In SNA, "degree" refers to the number of edges that are connected to the node. In 197 nodes of our network, the polarization of the connectional structure was highlighted by 712 self-loops of isolated tweets from zero degree (74.6% of the total edges). The letters in parentheses in Table 2 indicate user groups, and these are also used in the prefixes of users in Figure 1.

Table 2. Social graph metrics

Nodes	**197**
(S) Students in the course	65
(D) Students who had withdrawn from the course	10
(F) Students not in the course	10
(C) Social users on Twitter	112
Total edges	954
Unique edges	136
Edges with duplicates	818

Self-loops	712
Connected components	58
Reciprocated node pair ratio	0.0671
Reciprocated edge ratio	0.126
Maximum nodes in a connected component	27
Graph density	0.00412

While the number of maximum connected nodes was 27, the reciprocated edge ratio was 0.126. We speculated that tweets were distributed heterogeneously on the network, creating a close relationship with the selected partners.

3.2 Connections of users

Figure 1 displays a social group graph which was calculated by the Clauset-Newman-Moore cluster algorithm [24]. All the nodes were clustered into 29 social group graph groups (G1–G29). Although the graph density was low (0.00412, Table 2) due to the existence of 712 self-loops, the remaining 242 edges formed groups as shown in Figure 1. The larger nodes indicate users with at least 1,000 followers. The nodes that have no connections were mapped in the top-left group (G1). Although the students sent many messages to users with many followers, no hub from group (C) appeared in the social group graph.

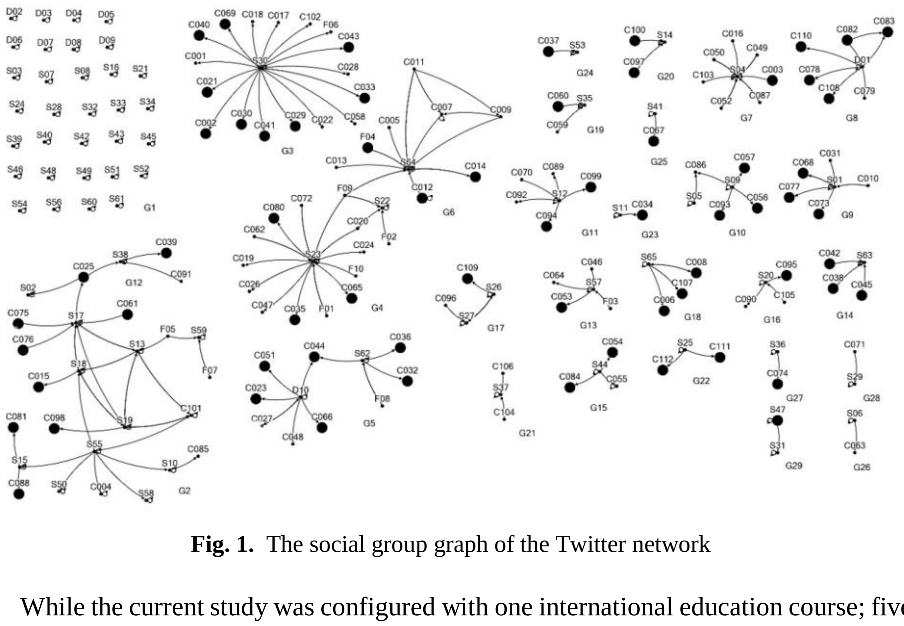

Fig. 1. The social group graph of the Twitter network

While the current study was configured with one international education course; five sessions on world issues; and 25 subtopics for assignments, a total of 28 social group graph groups (excluding G1) were formed. The result showed the emergence of a specific, focused scholarly discussion tweets that circulated across the network.

The dataset from this study was incorporated into the further investigation using ERGMs to identify the statistical evidence.

Table 3 shows the results of the calculation of ERGMs. The propensity of "nodematch.group" proved to be significantly negatively affected by the same node group, and "nodematch.graphgroup" was positively affected by the same group in the social group graph. Whereas the baseline of a connection probability in mode 2 was calculated to be 0.000178, the log odds of the connection increased when "nodematch.group" and "nodematch.graphgroup" were included. The probability reflected 0.01534 and 8.62 times more likelihood of connecting on this network. Consequently, a connection in the same social group graph group has a higher propensity to appear in the network than a connection in the same user group.

Table 3. Results of estimation of ERGMs regression

	Dependent variable: Estimate	
ERGMs term parameters	***Mode 1***	***Mode 2***
edges tweets	-5.065*** (0.086)	-8.634*** (0.500)
nodematch.group same group in S, D, F, and C	-1.570*** (0.230)	-2.178*** (0.233)
nodematch.graphgroup same group in G1- G29		6.653*** (0.508)

Note. *** p<.01, Standard errors are in the parentheses.

While the number of mutual connections was compared with generated random networks of the same density in the calculation of ERGMs (Table 4), the effect was strongly positive and significant in Modes 1 and 2. However, when we included term "gwesp" (the geometrically weighted edgewise shared partner), there was no significant relation with "mutual" in Mode 3 (see structure of terms in Figure 2). The positive propensity exhibited by "gwesp" indicated a tendency toward the transitive closure of multiple shared partners. Whereas the baseline of a connection probability in mode 1 was calculated to be 0.00362, the log odds of the connection increased when "mutual" was included. The probability was 0.128 and 35.4 times more likely to connect on this network.

Table 4. Results of estimation of ERGMs regression

	Dependent variable: Estimate		
ERGMs term parameters	***Mode 1***	***Mode 2***	***Mode 3***
edges	-5.619*** (0.085)	-5.619*** (0.001)	-5.566*** (0.081)
mutual reciprocal tweets	3.696*** (0.357)	3.680*** (0.016)	0.965 (1.252)
nodecov.follower number of followers		0.000 (0.000)	0.000 (0.000)
gwesp closure of transitive triads			1.786* (1.079)

Note. * p<.1; *** p<.01, Standard errors are in the parentheses.

On the other hand, while the baseline of a connection probability in mode 3 was calculated to be 0.00381, the log odds of the connection increased when “mutual” and “gwesp” were included. The probability reflected 0.0565 and 14.8 times more likelihood of connecting on this network. Consequently, a reciprocal connection had a higher propensity to appear in the network than a transitive triad connection structure. The result meant that users tended to form more pairs than pairs that were bridged by another same user (a gray node in Figure 2). The result was also consistent with the appearance of more star structure connections than triad connections, as shown in Figure 1.

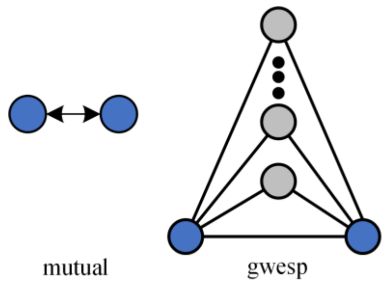

Fig. 2. Illustration of mutual and gwesp structural terms

3.3 Three connection types

Student activity records on Twitter were categorized into three connection types, each capturing the distinct performance of the students’ communication. The types were related to the recognition of existing and emerging connections based on the students’ selection of social users and friends or their decision to isolate. Their styles of connection on Twitter were classified into three types.

A: Crossing type: Students who established scholarly communication with social users who had more than 1,000 followers. Students could pass over the boundary of their network. The type included students whose tweets were either “replied to” or “retweeted.”

B: Private type: Students who only made connections with classmates in the course or their friends. They could not make any connection with users from other Twitter communities.

C: Isolation type: Students whose tweets were self-loops (i.e., single-node components) of isolated tweets. No other users were connected to them.

A: Crossing type. Since students searched for active Twitter users to target with their tweets, 56.3% of all the social media users who either retweeted or mentioned a student were users who had more than 1,000 followers.

Cases in which students had reciprocal communication with social twitter users

In Table 5, two cases are described in which students successfully communicated with social Twitter users. These messages involved concrete points of discussion that matched the responder’s interests. For instance, student S01 posed a question regarding a specific ordinance in their home country to a famous user. This showed that the student investigated the target Twitter user's messages before tweeting.

Table 5. Student communications with social Twitter users with at least 1,000 followers

Student (Language used in the tweet)	Social users	Communication
S64 (Japanese)	C014	A student reported on the number and situation of migrant workers in Saudi Arabia, and a social user from Saudi Arabia agreed that the number of migrant workers was increasing there.
S01 (Mongolian)	C068	The student asked about the toilet laws and the legal framework for bio-toileting in Mongolia. The social user replied that the related statements appear in the law on waste. Business sectors and organizations are required to establish facilities that do not pollute the soil, and there is no regulation on civil liability.

Table 6 shows cases in which students' tweets were retweeted by social Twitter users. The tweets involved different types of messages, including those providing information, expressing opinions, and asking for information. Although no contextual similarity among tweets was observed, all the tweets were academic and had informative contents.

Table 6. Tweets forwarded by social Twitter users with at least 1,000 followers

Student (Language used in the tweet)	Social users	Message in tweet
S02 (English)	C025	The message said that nutrition deficiency in childhood decreases the resistance against infection. The student explained that it is necessary for countries not only to cope with infections but also to provide food aid to infants.
S04 (Japanese)	C003	The statement said that, in China, the GDP is increasing and the poverty rate is decreasing.
S14 (Japanese)	C097 C100	An introduction to the famous Yellow vest movement (Gilet Jaune) and a discussion of the issue of disparity in immigrant communities in France.
S17 (Japanese)	C061 C075 C076	The student's opinion on why the degree of risk in travelling to Hong Kong was not level three. The student asked to learn more about the social movement there.
S35 (Japanese)	C059 C060	This message explained that the GNI > GDP in the Philippines due to foreign migrant workers and that there is a severe social security issue in the country. Additionally, fewer workers are migrating from the Philippines to Japan because of Japan's sluggish economy.
S38 (English)	C025	A statement that, globally, there have been fewer people living in slums over the years but that nearly 30% of the urban population still lives in slums.
S53 (Japanese)	C037	A message that, in Italy, the Gini coefficient has decreased, and the rate of enrollment in higher education has increased.
S63 (Japanese)	C038, C042, C045	A comparison of the situation in Japan (i.e., GNI > GDP) with other developed countries. A mention of the effects felt when major industries leave for other countries.
S65 (Japanese)	C008	A student's opinion stating that he agrees with the idea that the country's development did not increase the level of personal wealth in Brazil.

Note. GDP: gross domestic product; GNI: gross national income.

B: Private type. Tweets to classmates were not prohibited, but all the students knew that doing so was not the goal of the activity. Nevertheless, in the social group graph, the students in the private group tweeted to classmates and developed a group. Naim et al. [25] report that communication among students is accelerated when a course includes group learning. As our course required students to share time and space in jigsaw groups, the relational mechanism increased the likelihood of nodes being connected [26]. Thus, the creation of social capital with the help of social users was not straightforward; instead, the group environment in the classroom influenced students' online activities.

C: Isolation type. We observed that the tweets of many students in the isolated group (G1 in Figure 1) had the following characteristics: used only the lesson identifying hashtag (i.e., no message was included), and included a strategic request (e.g., "Please retweet (RT)"; "RT if you …"; "Spread the word!"; or "Pass it on!"). Such self-serving tweets were only intended to leave a footprint on Twitter, and the students who posted them did not search for or prepare information to share on Twitter.

3.4 Motivation

The 65 responses to the IMMS questionnaire were collected, and Table 7 shows the results. The internal consistency estimates using Cronbach's alpha were satisfactory (α = .93). The mean of total items (M =122.2, SD = 20.9) indicated that students were moderately motivated by the course content compared to other previous studies on online activity [27, 28].

Table 7. Results of the IMMS questionnaire

	Attention	Relevance	Confidence	Satisfaction	Total
No. of items	12	9	9	6	36
Range of scores	12–60	9–45	9–45	6–30	36–180
Midpoint	36	27	27	18	108
Mean (SD)	42.68 (7.41)	31.71 (6.21)	28.80 (5.29)	19.0 (5.22)	122.2 (20.9)
Cronbach's alpha	.80	.83	.68	.87	.93

Note. IMMS; Questionnaire items were proposed by Keller (2010).

A comparative analysis was conducted to understand the relationship between motivation scores and the three connection types. A significant difference between the three connection types using a one-way analysis of variance (ANOVA) test was detected (see Table 8).

Table 8. Results of the one-way ANOVA test

Source	Type III SS	*Df*	*MS*	*F*	*P*
Factor	3684.36	2	1342.18	4.10	< .05
Error	9823.82	30	327.46		
Total	12508.18	32			

Further, we conducted multiple group comparisons using Dunnett's test. Figure 3 shows that the crossing group scored significantly higher than the isolation group ($D_{crossing, isolation} = 2.57$; $p < .05$). The previous study also supported this result, and reported that users' motivations, not personality traits, had significant influence on integrated use of social media [29].

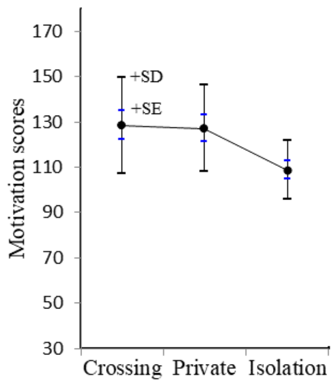

Fig. 3. Average motivation scores for student types

The result shows that higher levels of motivation in students contributed to the crossing of the border of the network.

4 Discussion

We calculated two SNA metrics to identify remarkable individuals in the social group graph. Eigenvector centrality is a measure used to identify how influential a particular individual is within a given network [30]. An individual with few connections has a higher eigenvector centrality if the individual has a connection with a node that is very well-connected. Although the students selected some social Twitter users with many followers, most of them were inactive or unresponsive, leading to lower eigenvector centrality in the network of this study. Another indicator, betweenness centrality, measures how many of the shortest paths exist between two users [31]. For example, a user with low betweenness has a smaller number of information collection paths. Other users with higher betweenness can collect the same information passing through different paths [32].

Figure 4 shows the relationship between betweenness centrality and eigenvector centrality, with the degree displayed as the node size. Black nodes show students of the crossing type, and grey nodes show students of the private type.

Most of the nodes were in an area with lower betweenness centrality and low eigenvector centrality. Although their tweets were linked to users in other communities, most of the connections were non-reciprocal and had limited connections to other students and limited impact on expanding the network.

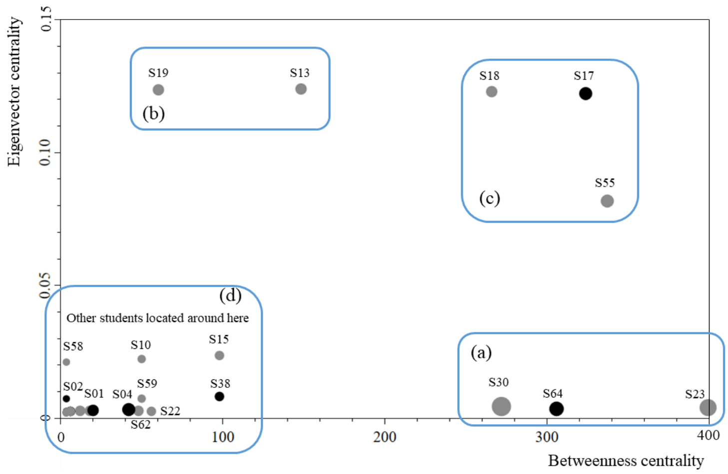

Fig. 4. Twitter network mapping of students' betweenness centrality (X-axis) and eigenvector centrality (Y-axis). *Note*. Black: crossing type, Gray: private type

However, three nodes (S30, S64, S23) were depicted as noticeable nodes that had higher betweenness centrality and lower eigenvector centrality. They located positions where information circulating in the network could easily be collected. The metrics of this location could explain the impact of the crossing type shown in Section 3.3 (A) and G6 in Figure 1. S64 encouraged small but explicit communication between social Twitter users and developed its own beneficial position to collect information. On the other hand, S30 and S23 had strategic spreading force but received limited replies due to insufficient investigation of target users to develop an intriguing tweet; they could be termed as spammers who tweeted excessively [33]. These cases looked different but were similar in terms of no connection to a popular user in the network. Area (a) in Figure 4 demonstrates the importance of developing socialization skills among students.

Two nodes (S19, S13) had lower betweenness centrality and higher eigenvector centrality, indicating that their tweets were connected to popular nodes. Area (b) in the figure explains a communication strategy in which increasing reciprocity to communicate with known users and identified as the private type. However, the strategy failed in network development in our study.

Because three nodes (S18, S17, S55) had higher betweenness centrality and higher eigenvector centrality, they contributed to the expansion of the network and became popular nodes in the network. Area (c) in the figure shows a case in which successfully incorporated ideas of social Twitter users resulted in network development. Although S19 and S55 did not have reciprocal connections with social Twitters users, they were inter-connected and experience of S17 could be shared.

The other students stayed in area (d) and the figure shows their distributed connections in the network.

Figure 4 also indicates the issue of developing a scholarly network in education. While three style types of students were defined as separated categories in Section 3.3, this study suggests that their connections were associated with one another regarding network development. Both outbound activities of students in area (a) and inbound activities of students in area (b) could be merged to expand the network that appeared in area (c). In other words, the crossing type and the private type appeared together in area (c) which was associated with clusters G2 and G12, as shown in in Figure 1.

Although students struggled to communicate with uses of other networks, the results of this study show how scholarly networks expand.

5 Conclusions

The results pertaining to students of the crossing type showed a clear effect on the way to expand a scholarly network. Since students could have both outbound and inbound connections, the difficulty of establishing the initial communication in the outbound activity was the problem. A previous study showed that students' social skills development and their preliminary investigation of other communities were essential in adapting their knowledge to other communities [34]; this is also seen in tweets from the crossing type students (S64 and S01). Another previous study reported that when a student faces users in a different network community, the information and its method of transfer should be adjusted in order to optimize its acceptance rate [9]. Motivation was identified and valued in 3.4 Section as the potential driving force to process this individual activity.

On the other hand, a student who could establish reciprocal tweets with a social Twitter user could be a bridge to introduce other students to another network. In order to increase the eigenvector centrality [35] and dissemination of information, the establishment of a connection between a bridge student and a popular student on the scholarly network is crucial. The conclusion is also in line with the importance of area (c) in Figure 4 and the increasing propensity toward triad connections shown in Section 3.2.

If these activities were coalesced in communications with social Twitter users, rich inner-communication will compensate for the requirement to develop social capital in the network. While the prevalence of self-loops (isolated tweets) was common on social media [11], the strategic empowerment of both outbound and inbound communication is greatly needed to expand students' learning in the network.

6 Declaration of conflicting interests

There are no conflicts of interest to declare.

7 Acknowledgment

This study was planned during our joint study at King Mongkut's Institute of Technology Ladkrabang (KMITL) in September, 2019, where Yoshida was invited as a guest researcher and worked with Petsangsri. The authors would like to thank the

School of Industrial Education and Technology, King Mongkut's Institute of Technology and a coordinator Dr. Jirarat Sitthiworachart for the opportunity.

This research was funded by JSPS KAKENHI, Grant-in-Aid for Challenging Research (Pioneering), Grant Number 20K20512.

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Article submitted 2021-09-29. Resubmitted 2022-02-28. Final acceptance 2022-02-28. Final version published as submitted by the authors.