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The Influence of Achievement Goals on the Centrality of Social Networks in Online Discussion

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The effectiveness of online discussions depends on how learners interact with each other. Instructors should provide adaptive supports to learners with difficulty in sharing their opinions and questions with others. Social network analysis can provide insights into the dynamics of interactions in online discussions. This study explored how learners' achievement goals affect learners' centrality in a social network. For this study, 107 undergraduates enrolled at a university in South Korea participated in the online discussion over a week. This study found that achievement goals influenced the time of first writing and the types of online discussion messages, which were grouped into active participation, critique-oriented, and idea-oriented clusters. Although achievement goals did not significantly influence in-degree centrality, the time of first writing and the message types had significant effects on it. For out-degree centrality, mastery approach goals and the message types had significant effects. Learners of the active participation cluster showed higher in-degree and out-degree centrality than the others. This study implies that instructors should help learners experience more meaningful interactions in online discussions by enhancing mastery approach goals and providing scaffoldings for early participation and diverse types of messages.

Keywords : Online discussion, Achievement goals, Social network analysis, Centrality

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Introduction

To experience meaningful learning in online discussions, learners have to share information, critically review various opinions, and strive to generate new ideas (Calvani et al., 2009). Since these kinds of activities are carried out through interactions with other learners, it is necessary to understand how social interactions take place to effectively support online discussions (Romero et al., 2013). It is expected that the interaction among learners can be effectively understood through social network analysis. It is an appropriate analysis method to investigate characteristics of interactions among learners, such as group dynamics and structure in online discussions by analyzing relationship information centered on nodes and links (Butts, 2008). This approach is differentiated from the traditional approach in research on online discussions, which analyzes quantitative information like the frequency of writing messages or qualitative information like the content of posts.

Particularly, it is important to understand where learners are located in a network in order to effectively support online discussions. The position of learners within the network could be used to identify those who are isolated from discussions and in need of support. Relatively isolated learners are more likely to experience insufficient interaction (Wasserman & Faust, 1994), access fewer learning resources (Klein et al., 2004), fail to build or develop knowledge (Wang, 2010), and ultimately make lower academic achievement (Jo et al., 2017; Macfadyen & Dawson, 2010). The concept of interaction structure is different from simple participation frequency, so writing a lot of messages does not directly make a learner more active or popular. Therefore, it is important to provide adequate support for these learners to become more engaged in discussions.

It is necessary to understand what factors influence the central role of participants in online discussions in order to identify learners who need help early and provide adaptive support, which can encourage more active participation and engagement in the discussion. Previous studies focused on how a learner's central position impacts learning achievement (Cho et al., 2007; Jo et al., 2017) and how learners are different from each other according to their centrality in a discussion network (Kim et al., 2021; Liu et al., 2017). They also paid attention to investigating the effects of specific interventions on learners' positions within the network such as online learning environment and role scripts (Carceller et al., 2015). However, most studies did not examine which individual differences were associated with how well learners are positioned within social networks in online discussion. Some studies identified factors such as gender, prior knowledge, and social relationships that can affect a learner's position and connections in the network (Cho et al., 2005; Liu et al., 2017), but there is still a lack of empirical research on the influence of individual psychological factors on learners' roles and integration within these networks.

Factors influencing centrality in online discussions

To understand how learners relate to one another in online discussions, it is necessary to analyze centrality through social network analysis. Degree centrality is the simplest way to calculate centrality and indicates the number of direct connections a learner has. For example, if two learners wrote ten messages each but one wrote them to one member and the other wrote two messages to five learners each, the latter has a higher centrality and more influence because of their more central position.

Degree centrality in social network analysis can be divided into two types: in-degree centrality and out-degree centrality. In-degree centrality indicates the number of direct messages that a learner received from other members in an online discussion. This indicator reflects the learner's acceptance, respect, reputation, and popularity within the network, and their opinions are considered relatively important (De Laat et al., 2007; Liu et al., 2017). On the other hand, out-degree centrality represents the number of direct messages that a learner sent to other members. This indicator reflects the learner's social influence, activeness, contribution, and expansiveness in the discussion (Liu et al., 2017). Learners with high out-degree centrality are more likely to experience flow and actively participate in the discussion (Liu et al., 2017). Analyzing centrality can help understand the individual positions of learners within the online discussion network.

Learners experience different learning processes in online discussions depending on their centrality. Learners with high centrality are expected to receive a lot of attention from other learners and actively participate in a discussion, while those with low centrality are expected to be isolated from others and passively participate in a discussion (Wasserman & Faust, 1994). Prior literature reported that the role of learners in online discussions also differs according to centrality. For example, in the study by Kim and Ketenci (2019), learners with a profile of high in-degree, out-degree, and betweenness centrality played the role of leaders in the discussion. They are reported to exhibit more transformational leadership and cognitive participation in asynchronous online discussions (Kim et al., 2020) and to display more cognitive effort to further modify the text during writing (Kim et al., 2021). In other studies, learners who play the role of a moderator or facilitator have significantly higher in-degree and out-degree centrality than those who do not (Shea et al., 2013; Xie et al., 2014). In addition, learners who are closely connected with other learners can easily access a lot of information and resources from a network (Klein et al., 2004). This means that learners with high centrality can more easily build knowledge by using many resources collected from many relationships. Wang (2010) found that learners at central positions in online learning environments tended to experience high quality and substantial interactions because they were engaged in negotiation of meanings to construct knowledge.

Centrality is determined by how learners participate in an online discussion. First, centrality could be influenced by how early they participate in the online discussion. This is because learners who occupy a central position from the initial stage of discussion are more likely to continue to occupy a central position later (Stepanyan et al., 2013). Chen and Huang (2019) found that learners with low in-degree centrality participated late in the online discussion. They did not receive many replies from other learners because they did not have enough time, while the learners with high centrality who participated in the early stage of the discussion exchanged many replies with other learners. In addition, according to the model of receiving a response message in an online discussion made by Zingaro and Oztok (2012), the earlier a message was written, the higher the likelihood of receiving a response. It was figured out that messages written earlier evoked more responses (Chen et al., 2020).

Second, the length of a message can also be considered as a significant indicator affecting centrality in online discussions. Hrastinski (2008) reviewed literature and found that message length is a commonly used indicator of participation in online discussions along with message frequency, message quality, and learner perception. For example, Chen and Caropreso (2004) measured the length of a message as one of the indicators of learning participation in online learning. However, some conflicting reports were made on the effect of message length on centrality. In a study by Zingaro and Oztok (2012), longer messages were more likely to be answered by other learners. On the other hand, Chen and Huang (2019) found that message length did not affect centrality.

Last, the types of online discussion messages can influence the in-degree centrality of social networks. For example, critical messages that are not consistent with other learners' opinions are reported to be highly responsive (Chen et al., 2020). This is because critique is one of the key factors that induce learners' cognitive conflict and reaction (Rooderkerk & Pauwels, 2016). In addition, if messages contain meaningful content or questions, they can get a lot of responses. Learners who write a lot of rich messages have a high tie strength with other learners on the network (Chung & Paredes, 2015). In addition, learners who play a role in mediating and facilitating discussions have high in-degree centrality (Shea et al., 2013; Xie et al., 2014).

Influence of achievement goals on online discussion

Learners have different levels of centrality, which is affected by gender (Giri et al., 2014; Liu et al., 2017), prior knowledge (Cho et al., 2007; Liu et al., 2017; Russo &

Koesten, 2005), and social relationships that have already been established before the discussion (Cho et al., 2005). Although there is a lack of research on how learners' motivation affects the centrality, it is expected that achievement goals will influence the centrality in online discussions. A number of empirical studies indicate that achievement goals influence learning process and outcomes.

Achievement goals mean the reason and purpose for a learner to perform a task (Pintrich, 2000). Achievement goals are classified into mastery goals and performance goals according to whether the standard of achievement is absolute or relative. In addition, depending on whether approach goals are positive or negative, it is divided into approach and avoidance. According to this 2x2 matrix, achievement goals can be classified into a mastery approach goal, a mastery avoidance goal, a performance approach goal, and a performance avoidance goal (Elliot, 1999; Pintrich, 2000). Learners with mastery approach goals strive to master the task and develop knowledge and ability, while learners with mastery avoidance goals tend to avoid situations in which they face their inability to master the task. Performance approach goals relate to proving relative excellence. On the other hand, learners with performance avoidance goals focus on avoiding exposing their failure to others. Literature suggests that mastery approach goals and performance approach goals are positively related to learning outcomes, but the performance avoidance goals have a negative relationship with learning outcomes (Barron & Harachiewicz, 2001; Elliot & McGregor, 2001).

In collaboration, learners can naturally get information about differences in perspectives and competencies with other learners. Learners differently accept the information according to their achievement goals (Nicholls et al., 1990). Learners with a mastery goal attempt to share information and reconcile conflicting perspectives with peers (Darnon et al., 2006; Levy et al., 2004) because they perceive peers as competent (Darnon et al., 2006). Lim and Lim (2020) found that mastery goals significantly positively predicted co-regulation that planed, monitored, and regulated their own and other group members' learning during group work. On the other hand, learners with performance goals tend to take on dominant behaviors

(Sommet et al., 2015; Yamaguchi, 2001), express their opinions more defensively (Poortvilet et al., 2007), and critically and aggressively respond to others (Levy et al., 2004; Poortvliet et al., 2007). In the study by Schoor and Bannert (2011), performance approach goals were related to group conflict in a computer supported collaborative learning. In addition, learners with performance avoidance goals adopt strategies to participate late in discussion to avoid being criticized (Hirst et al., 2009).

Achievement goals can directly influence the out-degree centrality of social networks. It was found that learners with performance goals prefer taking additional individual tasks rather than collaborating with other learners (Volet & Mansfield, 2006). In addition, approach goals seem to be positively correlated with out-degree centrality because prior studies found that mastery approach and performance approach goals were positively correlated with group participation (Lau et al., 2010) and behavioral engagement (Cho & Cho, 2014). On the other hand, there seems to be a negative correlation between avoidance goals and out-degree centrality. It was found that mastery avoidance and performance avoidance goals were negatively correlated with group participation (Lau et al., 2010) and behavioral engagement (Cho & Cho, 2014). Nevertheless, the influence of achievement goals on the centrality of social networks is not conclusive. Some studies found no significant influence of achievement goals on discussion activities. For example, Darnon et al. (2007) showed that achievement goals did not affect whether learners asked follow-up questions when other group members disagreed with them.

This study aims to investigate the influence of achievement goals on the centrality of social networks, which may be mediated by online discussion activities. This study can contribute to an in-depth understanding of the role of achievement goals in online discussion and provide educators and practitioners with insights on how to improve students' centrality in social networks. Specific research questions of the current study are as follows:

RQ1: What effects do achievement goals have on online discussion participation?

RQ2: What effects do achievement goals and online discussion participation have on learners' centrality in a social network?

Method

Participants

A total of 111 undergraduates, who took the Introduction to Education course in South Korea, participated in this study as part of their coursework. Four students who did not complete the online discussion task were excluded from the data analysis, so this study analyzed data collected from 107 students (females: 56, males: 51). As shown in Table 1, participants' mean age was 21.3 years (SD = 1.87), and the percentage of sophomores (45.79%) was higher than others. About half of the participants (50.47%) did not have online discussion experiences before this study.

Procedure and Context

During the 16-week offline course, Introduction to Education, there was one week dedicated to an online discussion. Before the discussion, a prior survey was conducted to collect background information of the participants and to measure their achievement goals. After the survey, students were randomly assigned to one of 12 groups, each of which consists of 9 to 10 learners, for online discussions. Learners were asked to upload at least one post on the online discussion board for a week in their discussion group, using a Moodle-based learning management system. A discussion topic was about educational policy on autonomous private high schools in Korea. The schools operate their own curriculum without subsidies from the government and are not subject to government interference in the selection of students and the setting of educational expenses. In order to prevent inequality in educational opportunities, a policy to phase out the designation of the schools was proposed and it emerged as a social issue in Korea.

Table 1
Demographics of participants

Variable	Values	Frequency	Percentage (%)
Gender	Female	56	52.34
	Male	51	47.66
School year	1 year	9	8.41
	2 years	49	45.79
	3 years	18	16.82
	4 years	17	15.89
	Etc.	6	5.61
Online discussion experience	None	54	50.47
	1-10 times	42	39.25
	11-20 times	1	.93

Instruments

To measure achievement goals of learners, we modified items validated by Park and Lee (2005). The instrument included thirty items across four achievement goals: a mastery approach goal (e.g. I feel great joy in learning new knowledge), a mastery avoidance goal (e.g. It is a waste of time to continue learning tasks which are hard to understand), a performance approach goal (e.g. I want to be a competent person who is better at learning than others), and a performance avoidance goal (e.g. I don't want to deal with the task that can make me embarrassed). All items were measured on a 5-point Likert scale. The Cronbach's alpha of each goal ranged from .76 to .9.

We developed the coding scheme by modifying the coding scheme of Weinberger and Fischer (2006) according to the context of this study (See Table 2). We coded several messages and discussed issues caused by the initial coding scheme and revised it accordingly. The refinement process was repeated several times until all of us were satisfied with the coding scheme, and six categories (idea, question, agreement, critique, integration, and socio-emotional) were developed to analyze idea units as

Table 2
Coding scheme for message type

Variable	Description	Example
Idea	Articulating thoughts to the group (Weinberger & Fischer, 2006)	▫ In my opinion, autonomous private high schools can interfere with social mobility
Question	Questioning for fact-seeking, clarification, alternative-view-seeking, and explanation-seeking (Ke et al., 2011)	▫ Have you defined what good education means to you?
Agreement	Agreeing with others without any justification (Cho et al., 2011)	▫ I think there are no logical loopholes in your opinion ▫ I agree with you
Critique	Challenging the idea of others by indicating its weakness or providing an alternative perspective (Cho et al., 2011)	▫ I disagree with you because it could be arithmetic justice, not for students
Integration	Balancing and advancing a preceding argument and counterargument (Weinberger & Fischer, 2006)	▫ You said that equality is important in education because it promotes social mobility. In other countries, private schools themselves are symbols of the class.
Socio-emotional interaction	Having the indicators of greeting, giving credit, and emotional expressions and sharing personal life experiences that do not contribute to knowledge sharing or construction (Ke et al., 2011)	▫ Thanks for sharing your personal experiences ▫ You deal well with statistics : D

shown in Table 2. Using the coding scheme, two researchers analyzed messages independently and reached a substantial agreement (Cohen's Kappa = .95). One message was coded for one category only. That is, there was no double coding.

Data analysis

Records of learners' online discussion activities were collected, including authors, timestamps, and content of the posts. A total of 305 posts written by 107 participants were collected. In order to analyze learners' online discussion activities, we made the variables of the time of first writing, length, message types, and degree centrality based on the posts. The time of first writing was calculated in units of days from the deadline. For example, it has a time value of 2 if the first post was posted two days before the due date, 0 if it was posted on the due date, and -1 if it was posted one day after the due date. The length was calculated as the average word length of posts written by each learner. The contents of posts were collected for analyzing the message types. Each post content was segmented into messages that contain only one meaning in order to analyze a message type. All posts collected were segmented into 1175 messages, and 46 off-task messages were excluded from the analysis, resulting in a total of 1129 messages being analyzed. Author who uploaded posts and received the reply was collected to measure degree centrality. The number of messages sent and received within each group was coded as a matrix. Then, in-degree and out-degree centrality were calculated through NetMiner, a social network analysis program.

In order to explore the influence of achievement goals on online discussion participation, multiple linear regression analysis, cluster analysis, and one-way ANOVA were conducted. First, multiple linear regression analysis was carried out to figure out the influence of achievement goals on the time of first writing and length. Next, cluster analysis and one-way ANOVA were conducted to understand the influence of achievement goals on the message types. The cluster analysis was executed to classify profiles of message types. The cluster analysis used the variables on the six types of online discussion messages which revised the skewness through the log transform. The analysis procedure began with hierarchical cluster analysis to determine the initial number of clusters. Subsequently, using the number of clusters identified from this analysis, non-hierarchical cluster analysis was carried out to classify the final clusters. In addition, one-way ANOVA was conducted to compare clusters. Lastly, another one-way ANOVA was conducted to explore the relationship between achievement goals and discussion message clusters.

Hierarchical regression analyses were conducted to test whether in-degree centrality and out-degree centrality were influenced by achievement goals, the time of first writing, length, and message types. The R^2 change was examined to evaluate the model. Two models were used; achievement goals were entered in the first model and the time of first writing, length, and message types were added in the second model. The three message type clusters which were the result of cluster analysis were entered in the hierarchical regression models as dummy-coded grouping factors to allow comparisons of the three clusters. The active participation (AP) cluster served as the reference group.

Results

In this study, the variables presented in Table 3 were analyzed. The variables consist of achievement goals (mastery approach, mastery avoidance, performance approach, and performance avoidance), online discussion participation (time of first writing, length, and message types including idea, question, agreement, critique, integration, and socio-emotional interaction), and centrality (in-degree centrality and out-degree centrality).

Table 3
Descriptive statistics of variables

Variables	*M*	*SD*	Variables	*M*	*SD*
Achievement goals			Online discussion participation		
Mastery approach	4.35	.64	*Time of first writing*	2.79	2.07
Mastery avoidance	2.85	.74	*Length of a post*	215.79	99.15
Performance approach	3.62	.94	*Idea*	4.43	3.84
Performance avoidance	3.37	.91	*Question*	.87	1.25
Centrality			*Agreement*	.73	1.04
In-degree centrality	.25	.21	*Critique*	1.96	2.30
Out-degree centrality	.25	.17	*Integration*	.50	.72
			Socio-emotional interaction	2.07	2.63

Influence of achievement goals on online discussion participation

Influence of achievement goals on the time of first writing and length

Regarding the first research question, multiple linear regression analyses were carried out to investigate the influence of achievement goals on the time of first writing and length (See Table 4). First, the multiple linear regression analysis was conducted to investigate the influence of achievement goals on the time of first writing. Although the regression model was not significant, $F(4, 102)=2.28$, $p=.066$, performance avoidance goals negatively influenced the time of first writing ($\beta=-.22$, $p=.037$). Next, the multiple linear regression was carried out to predict average message length with four achievement goals. The regression model was not statistically significant, $F(4, 102)=1.99$, $p=.102$.

Table 4
Results of multiple linear regression analysis of achievement goals affecting time of first writing and length

Achievement goals	Time of first writing			Length		
	B	*t*	*p*	*B*	*t*	*p*
Mastery approach	.14	1.21	.231	-.09	-.79	.431
Mastery avoidance	.04	.30	.764	.15	1.25	.214
Performance approach	.15	1.51	.135	.00	-.04	.969
Performance avoidance	-.22	-2.11	.037	.11	1.07	.289

Influence of achievement goals on message types

Regarding the first research question, cluster analysis and one-way ANOVA were conducted to explore the influence of achievement goals on online discussion message types. First, a cluster analysis was performed to figure out patterns that learners participated in the discussion. The dendrogram of hierarchical cluster analysis indicated that the proper number of clusters was three. Based on this result, non-hierarchical cluster analysis was conducted using the three clusters. As a result of the analysis, three clusters were derived as shown in Figure 1. The cluster that created all types of messages most actively was named AP (active participation cluster); another cluster that focused on writing critique messages and rarely on writing the other five types of messages was CO (critique-oriented cluster); and the last cluster, IO (idea-oriented cluster), posted a lot of messages expressing their ideas but showed little interest in writing other types of messages.

One-way ANOVA was conducted to investigate whether there was a difference in the frequency of writing message types among the clusters. As shown as Table 5, significant differences were found in all message types (ps<.001). According to the Bonferroni post hoc test results, AP and IO wrote significantly more idea messages than CO. AP and CO posted significantly more critical messages than IO. In addition, AP made significantly more question, agreement, integration, and socio-emotional interaction messages than CO and IO.

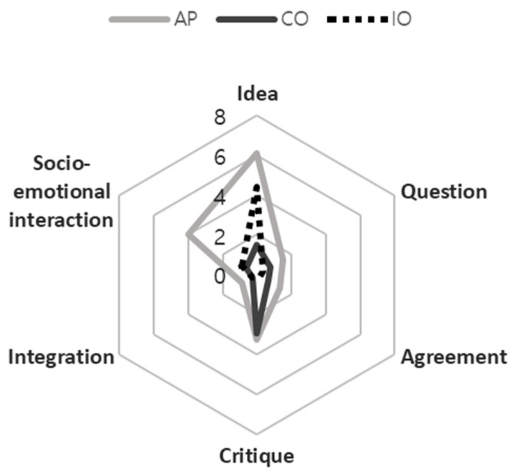

Figure 1. Profiles of message types for each cluster

Note) AP: active participation cluster, CO: critique-oriented cluster, IO: idea-oriented cluster

Table 5

Results of one-way ANOVA to compare message types between clusters

Message type	Mean(*SD*)			ANOVA		
	AP (n=42)	CO (n=23)	IO (n=42)	*F*	*p*	Post-hoc
Idea	6.07 (4.27)	1.48 (2.00)	4.40 (3.18)	13.04	<.001	AP,IO>CO
Question	1.48 (1.33)	.74 (1.42)	.33 (.72)	10.50	<.001	AP>CO,IO
Agreement	1.33 (1.24)	.65 (.78)	.17 (.49)	17.31	<.001	AP>CO,IO
Critique	3.24 (2.44)	2.96 (1.92)	.14 (.35)	36.29	<.001	AP,CO>IO
Integration	.86 (.84)	.26 (.62)	.26 (.45)	10.30	<.001	AP>CO,IO
Socio-emotional interaction	4.00 (3.13)	.65 (1.07)	.90 (1.08)	28.44	<.001	AP>CO,IO
Total	16.98 (8.64)	6.74 (3.39)	6.21 (4.00)			

Note) AP: active participation cluster, CO: critique-oriented cluster, IO: idea-oriented cluster

In order to compare achievement goals among the clusters, one-way ANOVA was carried out. As shown in Table 6, there was a significant difference in performance approach goals among the three clusters, $F(2, 104)=3.76$, $p=.026$. Learners in the AP cluster had higher performance approach goal than those in the CO, according to the Bonferroni post hoc test.

Table 6
Results of one-way ANOVA to compare learning motivation between clusters

Achievement goals	Mean(*SD*)			ANOVA		
	AP (n=42)	CO (n=23)	IO (n=42)	*F*	*p*	Post-hoc
Mastery approach	4.49 (.63)	4.13 (.63)	4.34 (.62)	2.57	.082	
Mastery avoidance	2.64 (.78)	2.99 (.71)	2.99 (.68)	3.05	.052	
Performance approach	3.88 (.92)	3.25 (1.12)	3.55 (.78)	3.76	.026	AP>CO
Performance avoidance	3.21 (.92)	3.46 (1.11)	3.47 (.77)	1.02	.363	

Note) AP: active participation cluster, CO: critique-oriented cluster, IO: idea-oriented cluster

Influence of achievement goals and online discussion participation on centrality

Influence of achievement goals and online discussion participation on in-degree centrality

Regarding the second research question, hierarchical regression analysis was conducted for in-degree centrality (see Table 7). Two different models were examined to understand how much achievement goals and online discussion participation could explain the dependent variable, in-degree centrality.

The first model was not statistically significant, while the second model was significant. In the first model, achievement goals accounted for 2% of in-degree centrality, and the influence of achievement goals was not significant, $F(4, 102)=.40$, $p=.805$.

The second model including achievement goals and online discussion participation variables as independent variables explained 34% of the in-degree centrality. This model significantly explained a further 32% of the dependent variable than the first model, $F(8, 98)=6.22$, $p<.001$. Learners who participated in the online discussion early received more messages than others ($p<.001$). Participants in AP had higher in-degree centrality than those in CO ($p=.031$) and IO ($p=.034$). When CO was designated as a reference group, there was no significant difference between CO and IO ($p=.76$).

Table 7

Results of hierarchical regression analysis on in-degree centrality

Variable	Model 1			Model 2		
	B	*t*	*p*	*B*	*t*	*p*
Mastery approach	-.05	-.38	.702	-.12	-1.22	.227
Mastery avoidance	-.03	-.28	.779	-.02	-.15	.882
Performance approach	.10	1.02	.312	-.03	-.29	.773
Performance avoidance	-.08	-.76	.448	.05	.52	.602
Time of first writing				.47	4.92	<.001
Length				.00	.04	.965
CO(dummy)				-.22	-2.19	.031
IO(dummy)				-.22	-2.15	.034
R2		.02			.34	
ΔF		.40			11.86	

Note) CO: critique-oriented cluster, IO: idea-oriented cluster

Influence of achievement goals and online discussion participation on out-degree centrality

Regarding the second research question, hierarchical regression analysis was conducted for out-degree centrality (see Table 8). Two different models were examined to understand how much achievement goals and online discussion participation could explain the dependent variable, out-degree centrality. All models were significant.

In the first model, achievement goals significantly accounted for 13% of out-degree centrality, $F(4, 102)=3.64$, $p=.008$. Mastery approach ($p=.013$) and performance approach goals ($p=.026$) positively influenced out-degree centrality.

In addition to achievement goals, online discussion participation variables including the time of first writing, length, and message types were entered in the second model. This model significantly explained a further 32% of the dependent variable than the first model, $F(8, 98)=9.89$, $p<.001$. Learners who had a higher mastery approach goal sent significantly more messages than the others ($p=.012$). In addition, participants in AP had higher out-degree centrality than those in CO and IP (ps<.001). When CO was designated as a reference group and analyzed, there was no significant difference between CO and IO ($p=.49$).

Table 8

Results of hierarchical regression analysis on out-degree centrality

Variable	Model 1			Model 2		
	B	*t*	*p*	*B*	*t*	*p*
Mastery approach	.29	2.54	.013	.24	2.56	.012
Mastery avoidance	.06	.53	.597	.16	1.68	.095
Performance approach	.21	2.25	.026	.07	.92	.360
Performance avoidance	-.07	-.66	.512	.04	.51	.609
Time of first writing				.17	1.95	.055
Length				-.13	-1.60	.114
CO(dummy)				-.39	-4.27	<.001
IO(dummy)				-.53	-5.57	<.001
R^2		.13			.45	
ΔF		3.64			14.24	

Note) CO: critique-oriented cluster, IO: idea-oriented cluster

Discussion

This study explored the influence of achievement goals on the centrality of social networks in an online discussion. This study found that achievement goals had a significant effect on message types. Learners with higher performance approach goals were more likely to belong to the AP, in which they wrote various types of messages. Previous studies have reported that learners with performance goals often react critically to other learners (Levy et al., 2004; Poortvliet et al., 2007), but this study found that the performance approach goal of CO was lower than that of AP. Achievement goals might have a complex effect on the message types. Although not statistically significant, the mastery approach goals of learners in AP were the highest among the three clusters. Previous studies have shown that approach goals are positively correlated with participation in collaborative learning (Lau et al., 2010; Cho & Cho, 2014). Unlike message types, the time of first writing and length were not significantly affected by achievement goals.

Achievement goals and online discussion participation had significant effects on centrality. First of all, learners with a higher mastery approach goal more actively sent messages to other learners. That is, they had a higher out-degree centrality. This is consistent with the results of previous studies that mastery approach goals are positively related to participation in collaborative learning (Cho & Cho, 2014; Lau et al., 2010). Learners with mastery goals view their peers as competent (Darnon et al., 2006) and attempt to share information and reconcile different perspectives with peers (Darnon et al., 2006; Levy et al., 2004). Therefore, they approach to interact actively with other learners for mastering a task, which leads to an increase in out-degree centrality.

In addition, the time of first writing and message types significantly influenced centrality. The timing of participation in an online discussion predicted in-degree centrality, which is similar to the results of previous studies that the earlier learners participate, the higher centrality they get (Chen & Huang, 2019; Stepanyan et al., 2013). Learners who participate late in the discussion are more likely to be isolated from the network and seldom experience meaningful interactions because they do not have enough time to send and receive messages. In addition, this study showed learners in AP, who wrote a lot of messages of all types, had higher in-degree and out-degree centrality compared to those in CO, which mainly uploaded critique messages, and IO, which mainly posted idea messages. Although there have been reports of previous studies that message types, such as opposing opinions, new information, and questions, provoke responses of different learners (Chung & Paredes, 2015; Shea et al., 2013; Xie et al., 2014), there have been few studies dealing with the effect of message type patterns. In this study, through cluster analysis and regression analysis, it was found that in-degree and out-degree centrality was higher in the AP cluster writing various types of messages than in the CO and IO clusters writing mainly specific types of messages. These results show that achievement goals have an indirect effect on centrality through participation timing and message types.

Conclusions

This study found that achievement goals not only had a direct effect on centrality but also had an indirect effect mediated by online discussion participation. To connect with others more in online discussion, learners need to have mastery approach or performance approach goals and participate in online discussions early, writing a variety of messages. Prior studies reported that achievement goals influenced how learners participate in group work (e.g. Darnon et al., 2006) and predicted that online discussion participation behaviors would be related to the centrality (e.g. Chen et al., 2020; Zingaro & Oztok, 2012). However, they did not empirically examine the prediction. In this study, the understanding of centrality was enhanced by demonstrating that achievement goals influenced the centrality in online discussion.

The results of this study give some implications for online discussion support. It is needed to support learners, who are marginalized from discussions, to have a mastery approach goal, participate in discussions earlier, and write a variety of messages. For this, it is necessary to develop a dashboard to support an online discussion, considering learners' achievement goals and discussion participation. Dashboards should provide visual feedback so that learners can focus on their positive growth and change rather than be aware of relative failures. However, many recent learning analytics studies suggest a dashboard that allows learners to easily compare their achievement or participation with other learners, not themselves (Beheshitha et al., 2016; Mochizuki et al., 2007; Tan et al., 2017). Leader boards are typical examples of dashboard design that facilitate comparison of performance among learners. It could also be useful to include items in the dashboard that allow learners to monitor and regulate their participation timing and types of messages in order to make more opportunities to interact with other learners (Han et al., 2021).

In addition, there is a need to help groups regulate their discussion participation. Collaboration is not just the sum of individual activities. It can be more effective to support group-level regulation than to support an individual learner's self-regulation in collaborative learning. For example, Grau and Whitebread (2012) found that groups with high socially shared regulation were more successful. In addition, Zheng et al. (2019) analyzed teams of college and high school students collaborating on STEM tasks online. They found that students who successfully completed the tasks analyzed, planned, and elaborated group tasks more than those who did not. In online discussions, it can be effective to encourage group members to ensure no one feels isolated and to provide help if necessary. Educators should guide their class to the appropriate discussion participation rules and provide them with scaffolding and scripts in order to support groups to regulate their participation in the discussion.

This study focused on the differences among individual learners and did not consider the influence of each group's characteristics because the variance among groups was not significantly large. So, the group effect was not controlled in this study. However, in some situations, the unique characteristics of a group can have a significant influence on centrality. For example, according to Giel and their colleagues (2021), learners tend to participate more in group meetings when group members share a similar level of mastery approach goals. In addition, this study was conducted in the context of higher education in which learners had diverse majors. Educators should be cautious when applying the findings of this study to other contexts like K-12 school. Future research needs to explore the influence of achievement goals on the centrality of social networks in diverse online discussion contexts, considering the influence of groups' characteristics. Lastly, this study has the limitation of not exploring how centrality affects learning outcomes in online discussions. Future research needs to empirically investigate the impact of centrality on learning outcomes.

References

Barron, K. E., & Harackiewicz, J. M. (2001). Achievement goals and optimal motivation: Testing multiple goal models. *Journal of Personality and Social Psychology, 80*, 706-722.

Beheshitha, S. S., Hatala, M., Gašević, D., & Joksimović, S. (2016). The Role of achievement goal orientations when studying effect of learning analytics visualizations. In Proceedings of the *6th International Learning Analytics* & *Knowledge Conference*, 54-63. ACM.

Butts, C., (2008). Social network analysis: A methodological introduction. *Asian Journal of Social Psychology, 11*(1), 13-41.

Calvani, A., Fini, A., Molino, M. and Ranieri, M. (2009) Visualizing and monitoring effective interactions in online collaborative groups. *British Journal of Educational Technology, 41*, 213-226.

Carceller, C., Dawson, S., & Lockyer, L. (2015). Social capital from online discussion forums: Differences between online and blended modes of delivery. *Australasian Journal of Educational Technology, 31*(2), 150-163.

Chen, B., & Huang, T. (2019). It is about timing: Network prestige in asynchronous online discussions. *Journal of Computer Assisted Learning, 35*, 503-515.

Chen, G., Lo, C. K., & Hu, L. (2020). Sustaining online academic discussions: Identifying the characteristics of messages that receive responses. *Computers* & *Education, 156*, 103938.

Chen, S-J. & Caropreso, E. J. (2004). Influence of personality on online discussion. *Journal of Interactive Online Learning, 3*(2), 1-17.

Cho, H., Gay, G., Davidson, B., & Ingraffea, A. (2007). Social networks, communication styles, and learning performance in a CSCL community. *Computers* & *Education, 49*(2), 309-329.

Cho, H., Lee, J.-S., Stefanone, M., & Gay, G. (2005). Development of computer-supported collaborative social networks in a distributed learning community. *Behavior & Information Technology, 24*(6), 435-447.

Cho, M-H., & Cho, Y. (2014). Instructor scaffolding for interaction and students' academic engagement in online leaning: Mediating role of perceived online class goal structures. *The Internet and Higher Education, 21*, 25-30.

Cho, Y. H., Lee, J., & Jonassen, D. H. (2011). The role of tasks and epistemological beliefs in online peer questioning. *Computers* & *Education, 56*(1), 112-126.

Chung, K. S. K., & Paredes, W. C. (2015). Towards a social networks model for online learning & performance. *Educational Technology* & *Society, 18*(3), 240–253.

Darnon, C., Butera, F., & Harackiewicz, J. M. (2007). Achivement goals in social interactions: Learning with mastery vs. performance goals. *Motivation and Emotion, 31*, 61-70.

Darnon, C., Muller, D., Schrager, S., Pannuzzo, N., & Butera, F. (2006). Mastery and performance goals predict epistemic and relational conflict regulation. *Journal of Educational Psychology, 98*, 766-776.

De Laat, M., Lally, V., Lipponen, L., Simons, R. J. (2007). Investigating patterns of interaction in networked learning and computer-supported collaborative learning. *International Journal of Computer-Supported Collaborative Learning, 2*, 87-103.

Elliot, A. J. (1999). Approach and avoidance motivation and achievement goals. *Educational Psychologist, 34*, 169-189.

Elliot, A. J., & McGregor, H. A. (2001). A 2x2 achievement goal framework. *Journal of Personality and Social Psychology, 80*, 501-519.

Giel, L. I. S., Noordzij, G., Noordegraaf-Eelens, L., & Denktaş S. (2021). When birds of the same feather fly together: the impact of achievement goal compatibility in collaborative learning. *Educational Psychology, 41*(3), 79-98.

Giri, B. E., Manongga, D., & Iriani, A. (2014). Using social networking analysis (SNA) to analyze collaboration between students (case study: students of open university in Kupang). *International Journal of Computer Applications, 85*(1), 44-49.

Grau, V., & Whitebread, D. (2012). Self and social regulation of learning during collaborative activities in the classroom: The interplay of individual and group cognition. *Learning and Instruction, 22*(6), 401-412.

Han, J., Kim, K. H., Rhee, W., & Cho, Y. H. (2021). Learning analytics dashboards for adaptive support in face-to-face collaborative argumentation. *Computers and Education, 163*, 104041.

Hirst, G., Van Knippenberg, D., & Zhou, J. (2009). A cross-level perspective on employee creativity: Goal orientation, team learning behavior, and individual creativity. *Academy of Management Journal, 52*(2), 280-293.

Hrastinski, S. (2008). What is online learning participation? A literature review. *Computers* & *Education, 51*, 1755-1765.

Jo, I., Park, Y., & Lee, H. (2017). Three interaction patterns on asynchronous online discussion behaviours: A methodological comparison. *Journal of Computer Assisted Learning, 33*(2), 106-122.

Kim, M. K., & Ketenci, T. (2019). Learner participation profiles in an asynchronous online collaboration context. *The Internet and Higher Education, 31*, 62-76.

Kim, M. K., Wang, Y., & Ketenci, T. (2020). Who are online learning leaders? Piloting a leader identification method(LIM). *Computers in Human Behavior. 105*, 106205.

Kim, M., K., Lee, I. H., & Kim, S. M. (2021). A longitudinal examination of temporal and iterative relationships among learner engagement dimensions during online discussion. *Journal of Computers in Education, 8*, 63-86.

Klein, K., Lim, B-C., Saltz, J. L., & Mayer, D. M. (2004). How do they get there? An examination of the antecedents of centrality in team networks. *Academy of Management Journal, 47*, 952-963.

Lau, S., Liem, A. D., & Nie, Y. (2010). Task- and self-related pathways to deep learning: The mediating role of achievement goals, classroom attentiveness, and group participation. *British Journal of Educational Psychology, 78*(4), 639-662.

Levy, I., Kaplan, A. & Patrick, H. (2004). Early adolescents' achievement goals, social status, and attitudes towards cooperation with peers. *Social Psychology of Education, 7*, 127-159.

Lim, J. Y., & Lim, K. Y. (2020). Co-regulation in collaborative learning: Grounded in achievement goal theory. *International Journal of Educational Research, 103*, 101621.

Liu, C. C., Chen, Y. C., & Tai, S. J. D. (2017). A social network analysis on elementary student engagement in the networked creation community. *Computers* &

Education, 115, 114-125.

Macfadyen, L. P., & Dawson, S. (2010). Mining LMS data to develop an "early warning system" for educators: A proof of concept. *Computers* & *Education, 54*(2), 588-599.

Memon, N., Xu, J. J., Hicks, D. L., & Chen, H. (2010). Social network data mining: Research questions, techniques, and applications. In N. Memon, J. J. Xu, D. L. Hicks, & H. Chen (Eds.). *Data mining for social network data* (pp. 1-8). Springer.

Mochizuki, T., Kato, H., Fujitani, S., Yaegashi, K., Hisamatsu, S., Nagata, T., Nakahara, J., Nishimori, T., & Suzuki, M. (2007). Promotion of self-assessment for learners in online discussion using the visualization software. In N. Lambropoulos, & P. Zaphiris (Eds.), *User-centered design of online learning communities* (pp. 365-397). Information Science Publishing.

Nicholls, J.G., Cobb, P., Wood, T., Yackel, E. Patashnick, P. (1990). Assessing students' theories of success in mathematics: Individual and classroom differences. *Journal for Research in Mathematics Education, 21*, 109-122.

Park, B-G., & Lee, J-U. (2005). Development and validation of a 2x2 achievement goal orientation scale. *The Korean Journal of Educational Psychology, 19*(1), 327-352.

Pintrich, P. R. (2000). An achievement goal theory perspective on issues in motivation terminology, theory, and research. *Contemporary Educational Psychology, 25*, 92-104.

Poortvliet, P. M., Janssen, O., Van Yperen, N. W., & Van de Vliert, E. (2007). Achievement goals and interpersonal behavior: How mastery and performance goals shape information exchange. *Personality and Social Psychology Bulletin, 33*, 1435-1447.

Romero, C., López, M.-I., Luna, J.-M., & Ventura, S. (2013). Predicting students' final performance from participation in on-line discussion forums. *Computers* & *Education, 68*, 458-472.

Rooderkerk, R.P. & Pauwels, K.H. (2016). No comment?! the drivers of reactions to online posts in professional groups. *Journal of Interactive Marketing, 35*, 1-15.

Russo, T. C., & Koesten, J. (2005). Prestige, centrality, and learning: A social network analysis of an online class. *Communication Education, 54*(3), 254-261.

Schoor, C. & Bannert, M. (2011). Motivation in a computer-supported collaborative learning scenario and its impact on learning activities and knowledge acquisition. *Learning and Instruction, 21*(4), 560-573.

Shea, P., Hayes, S., Vickers, J., Gozza-Cohen, M., Uzuner, S., Mehta, R., … Rangan, P. (2010). A re-examination of the community of inquiry framework: Social network and content analysis. *Internet and Higher Education, 13*(1), 10-21.

Sommet, N., Darnon, C., & Butera, F. (2015). To confirm or to conform? Performance goals as a regulator of conflict with more-competent others. *Journal of Educational Psychology, 107*, 580-598.

Stepanyan, K., Mather, R. and Dalrymple, R. (2013). Culture, role and group work: A social network analysis perspective on an online collaborative course. *British Journal of Educational Technology, 45*(4), 676-693.

Tan, J. P. L., Koh, E., Jonathan, C. R., & Yang, S. (2017). Learner dashboards a double-edged sword? Students' sensemaking of a collaborative critical reading and learning analytics environment for fostering 21st century literacies. *Journal of Learning Analytics, 4*(1), 117-140.

Wang, L. (2010). How social network position relates to knowledge building in online learning communities? *Frontiers of Education in China, 5*(1), 4-25.

Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications* (Vol. 8). Cambridge University Press.

Weinberger, A., & Fischer, F. (2006). A framework to analyze argumentative knowledge construction in computer-supported collaborative learning. *Computers* & *Education, 46*(1), 71-95.

Xie, K., Yu, C., & Bradshaw, A. C. (2014). Impacts of role assignment and participation in asynchronous discussions in college-level online classes. *Internet and Higher Education, 20*, 10-19.

Yamaguchi, R. (2001). Children's learning groups: A study of emergent leadership, dominance, and group effectiveness. *Small Group Research, 32*, 671-697.

Zheng, J., Xing, W., & Zhu, GX. (2019). Examining sequential patterns of self- and socially shared regulation of STEM learning in a CSCL environment. *Computers & Education, 136*, 34-48.

Zingaro, D., & Oztok, M. (2012). Interaction in an asynchronous online course: A synthesis of quantitative predictors. *Journal of Asynchronous Learning Networks, 16*(4), 71-82.

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