**Volume 15, No. 3**
May 2017
ISSN: 1545-679X

# INFORMATION SYSTEMS EDUCATION JOURNAL

In this issue:

**4. Java vs. Python Coverage of Introductory Programming Concepts: A Textbook Analysis**
Kirby McMaster, Weber State University
Samuel Sambasivam, Azusa Pacific University
Brian Rague, Weber State University
Stuart Wolthuis, Brigham Young University - Hawaii

**14. Agile Learning: Sprinting Through the Semester**
Guido Lang, Quinnipiac University

**22. Testing Frequency in an Introductory Computer Programming Course**
Joni K. Adkins, Northwest Missouri State University
Diana R. Linville, Northwest Missouri State University

**29. Pursuing a Vendor-Endorsed ERP Award for Better Job Prospect: Students' Perceptions**
LeeAnn Kung, Rowan University
Hsiang Jui Kung, Georgia Southern University

**42. Developing an Approach to Harvesting, Cleaning, and Analyzing Data from Twitter Using R**
Stephen Hill, University of North Carolina Wilmington
Rebecca Scott, Texas Tech University

**55. Microsoft Excel®: Is It An Important Job Skill for College Graduates?**
Sam K. Formby, Appalachian State University
B. Dawn Medlin, Appalachian State University
Virginia Ellington, Appalachian State University

**64. Comparing Student Interaction in Asynchronous Online Discussions and in Face-to-Face Settings: A Network Perspective**
Elahe Javadi, Illinois State University
Judith Gebauer, University of North Carolina Wilmington
Nancy L. Novotny, Illinois State University

The **Information Systems Education Journal** (ISEDJ) is a double-blind peer-reviewed academic journal published by **EDSIG**, the Education Special Interest Group of AITP, the Association of Information Technology Professionals (Chicago, Illinois). Publishing frequency is six times per year. The first year of publication was 2003.

ISEDJ is published online (http://isedj.org). Our sister publication, the Proceedings of EDSIGCon (http://www.edsigcon.org) features all papers, panels, workshops, and presentations from the conference.

The journal acceptance review process involves a minimum of three double-blind peer reviews, where both the reviewer is not aware of the identities of the authors and the authors are not aware of the identities of the reviewers. The initial reviews happen before the conference. At that point papers are divided into award papers (top 15%), other journal papers (top 30%), unsettled papers, and non-journal papers. The unsettled papers are subjected to a second round of blind peer review to establish whether they will be accepted to the journal or not. Those papers that are deemed of sufficient quality are accepted for publication in the ISEDJ journal. Currently the target acceptance rate for the journal is under 40%.

Information Systems Education Journal is pleased to be listed in the 1st Edition of Cabell's Directory of Publishing Opportunities in Educational Technology and Library Science, in both the electronic and printed editions. Questions should be addressed to the editor at editor@isedj.org or the publisher at publisher@isedj.org. Special thanks to members of AITP-EDSIG who perform the editorial and review processes for ISEDJ.

# Comparing Student Interaction in Asynchronous Online Discussions and in Face-to-Face Settings: A Network Perspective

Elahe Javadi,
ejavadi@ilstu.edu
School of Information Technology
Illinois State University
Normal, IL 61790

Judith Gebauer
gebauerj@uncw.edu
Cameron School of Business, ISOM Department
University of North Carolina Wilmington
Wilmington, NC 28403, USA

Nancy L. Novotny
nlnovot@ilstu.edu
Mennonite College of Nursing
Illinois State University
Normal, IL 61790

**Abstract**

Online discussions enable peer-learning by allowing students to communicate ideas on what they have learned in and beyond the classroom. Peer-learning through online discussions is fostered when online discussions are interactive. Interactivity occurs when students refer to and use perspectives shared by peers, and elaborate, respond to, or propose alternative views to those shared by others. Open interactions in online discussions require students to choose whom they communicate with in the discussion forums. This study examines the extent to which the patterns of student-to-student interactions in online discussions resemble student interactions with the same peers in face-to-face settings. Online discussion data were collected in six sections of an introductory IS course over three semesters. Each section's dataset contains data from four online discussions among students, as well as the results of two familiarity surveys administered at the beginning and at the end of the semester. The results of the data analysis suggest a relationship between face-to-face interactions and patterns of online group idea sharing and integration. Understanding the structure and dynamics of interactions in online discussions can provide design guidelines to help overcome inherent familiarity fault-lines in classes, and to improve the extent and quality of peer-learning in online discussions.

**Keywords:** Asynchronous online discussions, interaction, familiarity, peer-learning

## 1. INTRODUCTION

Learning management systems (LMSs) are used extensively in higher education (Waters & Gasson, 2006). LMSs provide a platform where instructors and students can share resources, creative works, and opinions on course-related topics. LMSs' asynchronous online discussion

(AOD) tools support peer-learning because they can help remove obstacles such as production blocking and cognitive interference that often exist in verbal face-to-face and synchronous discussions. To enhance peer-learning, interactivity must be fostered. Interactions in AODs occur when students refer to and use ideas posted by their classmates, and when they provide elaborations, responses, counter-arguments, or alternatives thereto (Gruenfeld & Hollingshead, 1993; De Vreede, Briggs, van Duin, & Enserink, 2010). To elaborate and respond, students must attend to each other's ideas (Gruenfeld, Mannix, Williams, & Neale, 1996). They must also reciprocally value ideas in order to afford the cognitive efforts necessary to elaborate (Gruenfeld et al., 1996). In other words, elaborations require attention to the ideas of others as an enabling factor, and valuing others' ideas as a motivational factor (Javadi, Gebauer, & Mahoney, 2013). Previous research on group brainstorming and decision making provides insights into how the characteristics of a group affect group processes, such as information sharing and processing, elaboration, and consensus making. Homan, Van Knippenberg, Van Kleef, & De Dreu (2007), for instance, studied groups in which members possessed diverse information and discovered that fostering pro-diversity beliefs enhanced information elaboration in those groups. Prior research studies have also examined how familiarity among members and group social ties may influence cognitive processes that underlie information integration (Gruenfeld et al., 1996; Goodman & Leyden, 1991). Gruenfeld et al. (1996), for example, compared groups with different levels of familiarity among their members and found that while familiar groups were more effective in information sharing, unfamiliar groups were more effective in information integration. Prior literature has also shown that people tend to cluster around members who they feel most comfortable with (Cunningham et al. 2012). Clustering around familiar partners in online settings may lead to segmentation within discussions that can again limit the breadth and depth of peer-learning in AODs.

Because familiarity has been found to affect information sharing and information integration—two critical processes for creating effective group discussions—the current research examines the association between face-to-face interactions and interactions in online discussions applying social network analysis (SNA) (Gasson & Waters, 2011; Borgatti, Everett & Freeman, 2002). SNA methods have been used in prior literature to study the make-up of online discussions. Waters and Gasson (2012) used SNA to study the effect of course scaffolding on AODs. They specifically examined impacts of instructions given to students (general vs. structured), number of posts by course instructor, and level of moderation by the instructor (low vs. high) in relation to structure of the interactions network in online course discussions. To measure extent and quality of interactions in online course discussions, Waters and Gasson (2012) quantified number of messages, participants in threads, and maximum depth of threads. They also included behavioral measures to distinguish between peer-to-peer versus broadcast messages, and between student-to-student versus student-to-instructor interactions.

The current research focuses on how face-to-face familiarity among students relates with patterns of interactions in online course discussions. Therefore, our main research question is to what extent the structure and dynamics of student interactions in online discussions resemble the structure and dynamics of student face-to-face interactions. We operationalize our research question with two hypotheses:

***Hypothesis 1:*** *The structure of student interaction in online discussions resembles the structure of student face-to-face interaction.*

***Hypothesis 2:*** *The evolution of student interaction in online discussions resembles the evolution of student face-to-face interaction.*

Hypothesis 1 states that the structural properties of online interaction networks are expected to resemble the structural properties of face-to-face interaction networks. Hypothesis 2 implies that as the four commenting networks and the two face-to-face familiarity networks are examined, the earlier commenting networks will show more similarity to the first face-to-face familiarity network while the later discussions networks are expected to show more similarity to the second face-to-face familiarity network. In other words, as online commenting interactions evolve over the course of the semester, that evolution is expected to resemble the evolution of face-to-face familiarity links among the students.

## 2. METHOD

Student *interaction in online discussions* was operationalized based on the comments that students posted on each other's ideas during four online discussions over a 16-week semester; *interaction in face-to-face* was measured based on a familiarity survey administered at the beginning and at the end of the semester. The survey asked students to self-report the extent to which they knew/interacted with other students at the time of the survey. Online and face-to-face interaction networks were then compared using SNA methods.

Several measures of network structures were examined to compare the structures of online and face-to-face interactions. To examine the evolution of online interaction networks we compared the commenting interactions during four discussions that occurred at different times during the semester. The evolution of face-to-face interactions was examined by comparing networks of familiarity measured at the beginning and at the end of the semester. The structures of the four commenting and two familiarity networks were then compared, taking into account the time at which they were measured. Our hope is that a better understanding of the associations between online and face-to-face interactions can guide the design and implementation of interventions that could bridge familiarity fault-lines and thus promote a higher level of peer-learning in AODs.

**Data Set**

Research data were collected from six sections of a 200-level course. The collected data include student interactions during four online discussions that took place on the course's LMS. The four discussions comprised twenty percent of the final course grade (five percent each). Per instructions, students were encouraged to think critically about a specific course-related topic and were asked to engage in an online conversation with their classmates. To start the conversation, the instructor used a prompt related to the topic. The articles and topics for each of the four discussions were identical across the six course sections. For each student, a discussion assignment involved posting one original idea and four comments on the contributions of other students. Each discussion was completed in two phases. During the 1st phase all students were required to post their original analysis; and during the 2nd phase, students were required to post four comments on any of the original analyses that were posted in the 1st phase. The two-phase design was chosen to remove the impact of 'time of post' on the extent to which a certain post received comment from others. The instructor provided students with examples of acceptable posts and comments. For instance, "*I agree with the authors' argument that the world is spiky and not flat, but I find the evidence insufficient, mainly because the authors have focused on the number of patents, which is only one indicator of creative production*," was listed as an acceptable post. In contrast, "*I liked the article*," and "*I also think the world is spiky*," were listed as unacceptable posts. For the comments, "*I agree with you, but if I look closer, I find it difficult to measure other forms of creative production. Number of patents is not a perfect indicator, but it is a precise and reliable indicator*," was listed as an acceptable comment and, "*I agree*," as an unacceptable comment.

The familiarity survey was administered twice: at the beginning of the semester and at the end. The first questionnaire asked students to report the extent to which they knew each of their classmates before attending the class, using a scale from 1 to 5. The questionnaire had a table with one row for each student and five columns that indicated the five levels for measuring familiarity. Students were expected to fill the table, one row at a time (keeping the row for their own names empty), and put an X mark on the column which best explained their face-to-face interactions with the student whose name was written in that row. The level 1 anchor represented "not familiar" (*never heard of or have seen this person before attending this class*) while the level 5 anchor represented "very familiar" (*have known this person and/or worked with them before attending this class*). The second familiarity questionnaire asked students to report the extent to which they knew each of their classmates at the end of the semester. The new descriptions for the 5-point scale read as follows: Not familiar (*I don't know this person and I have not talked with them during the semester*) for level 1, and Very familiar (*I know this person and I have worked with them during the semester*) for level 5. An assumption was that the in-class group-based activities, a four-week group project, and the instructor's use of a grouping mechanism to encourage students to partner with less-familiar classmates, would contribute to a higher level of interpersonal recognition reported at the end of the semester.

To compare the structure and evolution of student interactions in the online discussions and interactions in face-to-face, two-dimensional matrices of the commenting links and familiarity links were constructed. The two-dimensional matrices were organized using the student codes in the first row and in the first column. For a course section with $n$ students, the matrix therefore resulted in $n \times n$ cells. If student $i$ commented on student j's post $m$ times, then the entry in cell $(i,j)$ was set as $m$. In a subset of analyses in this study, a binary version of commenting matrices were used. In binary matrices, cell values are set as 1 for cell ***(i,j)*** if student ***i*** ever commented on student ***j***'s post and 0 if s/he did not. Familiarity links were stored in similar two-dimensional ***n×n*** matrices. If a student ***i*** rated their familiarity with student ***j*** as ***r*** (on a scale from 1 to 5), then the entry in cell ***(i,j)*** was set to ***r***. In a subset of analyses in this study, the familiarity information was noted in a binary matrix in which a 1 in cell ***(i,j)*** indicates that student ***i*** provided a rating for his/her familiarity with student ***j***, at a level of 3 or higher, whereas a 0 in cell ***(i,j)*** indicates that the rating was less than 3.

### Analyses

Social Network Analysis (SNA) methods and measures were employed to compare the interactions in the online discussions and face-to-face interactions. Social network analyses are generally useful to examine the connections among entities (e.g., individuals, institutions, research papers) who together comprise a network. Connections can be of different types, including trust, friendship, merger, or citations. In the current study, two types of connections are of particular interest: commenting and familiarity.

The network analyses included four steps. In the first step, we assessed the online interactions during the four discussions based on four measures of network structures: (1) density (2) centrality, (3) reciprocity, and (4) clustering coefficient. The four measures and their implications for online discussions are explained in the next section. In the second step, we performed node-level analyses on the commenting and familiarity matrices to assess the correlation between a particular student's statuses in the commenting networks and their statuses in the familiarity networks. In particular, we examined the correlation between the number of comments received and the number of familiarity links received for each student, as well as the correlation between the reciprocity for comments and familiarity links for each student. In the third step, we performed dyadic analyses to assess the similarities between interactions in the commenting networks and in the familiarity networks when compared at the dyadic level. Lastly, mixed dyadic-nodal analyses were performed to assess the associations between commenting connections and familiarity, i.e., students' tendency to comment more frequently on ideas posted by familiar others than on those by non-familiar others. The results of each analysis will be described in the following sections.

## 3. RESULTS AND DISCUSSION

### Network-Level Analyses

We utilize two sets of directed graphs, one set describes the online interactions (Figure 1) and the other set summarizes the face-to-face interactions (Figure 2). Figure 1 describes the structure of the online discussion networks (D1 – D4) based on the measures of density, centrality, reciprocity, and clustering coefficient, in each of the six course sections (S1 – S6).

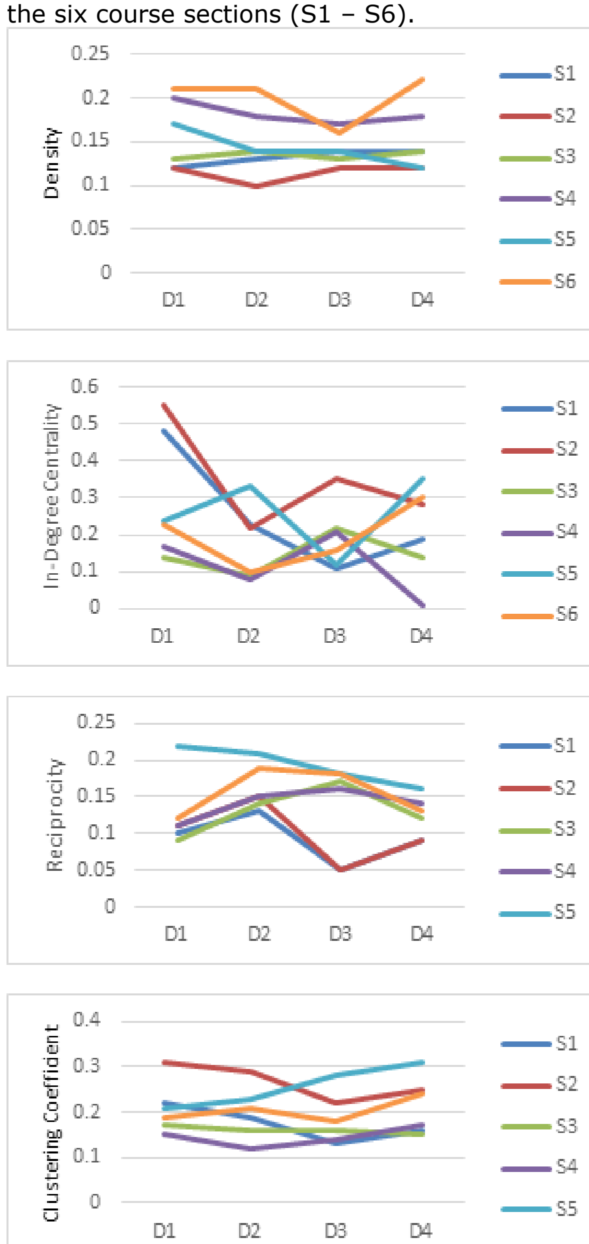


**Figure 1:** Four Measures of Discussion Network Structures (Discussions D1-D4, Sections S1-S6)

Because students were required to post four comments during each round of discussion, the number of comments posted by each student (i.e., out-degree measures) bears little information. However, it was useful to examine the differences in the number of comments that each student received on his/her posts; i.e., in-degree measures for the nodes in the discussion graphs.

Figure 2 illustrates the changes in density measures of network structures in face-to-face interactions between the beginning and end of the semester within each of the six course sections.

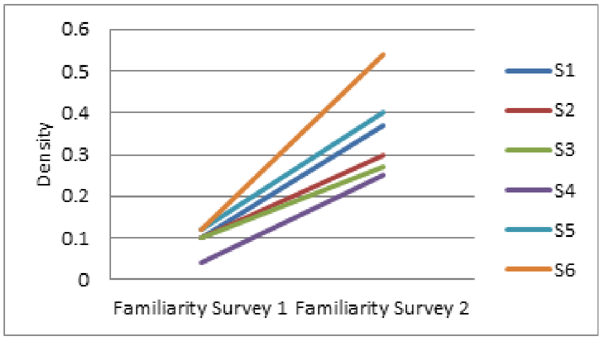

**Figure 2:** Network Density Measures

**Node-Level Analyses**

To examine hypothesis 1, node-level analyses were performed on the commenting and familiarity matrices. Node-level analysis examines the extent to which a certain student's statuses—as measured by centrality and reciprocity—in discussion and familiarity networks are correlated. Specifically, we examined the correlation between the number of comments received and existence of a familiarity link with each member in the discussion. In addition, we calculated the correlation between the extent to which a student's comments on other students' comments was reciprocated and the number of the connections (outgoing and incoming) that the student had in the familiarity network. Therefore, the two sets of correlation measures are: (1) the correlation between in-degree centrality measure in the discussion networks and the in-degree centrality measure in the familiarity network (Table 1 in the Appendix); and (2) the correlation between the reciprocity measures in the discussion networks and the degree of centrality in the familiarity networks (Table 2 in the Appendix).

In line with hypothesis 1, positive correlations exist in 84% of the cells in Table 1 (shaded cells), which means that 16% of the observations are not consistent with hypothesis 1. While the results do not fully corroborate hypothesis 1, the positive correlation in the majority of the cells in Table 1 suggests a tendency of face-to-face familiarity to transcend into online interactions, but also calls for additional analysis. Table 2 shows the correlation between reciprocity measures and degree centralizations. Positive correlation is observed in 74% of the cells, which means that 26% of the observations are not consistent with hypothesis 1. Although not fully conclusive, the mere presence of correlation is an intriguing observation that the extent of reciprocity is associated with popularity in class for the majority of the class discussions.

**Dyad-Level Analyses**

To better understand the association between the dyadic relationships in the discussion and familiarity networks, we used the Jaccard coefficient (Borgatti et al. 2002; Jaccard, 1912), a measure that can show the extent to which a dyad in one network (discussion) co-exists with its corresponding dyad in another network (familiarity). The coefficient is at its maximum of 1, if for every student ***j*** that student ***i*** has expressed familiarity with, student ***i*** has also commented on at least one of student ***j***'s posts. Moreover, for every student ***j*** that student ***i*** has expressed no familiarity with, student ***i*** has refrained from commenting on student ***j***'s posts. In technical terms, to calculate Jaccard's similarity coefficient for two binary vectors, the following are counted: total number of times that an element is 1 in both vectors ($J_{11}$) and total number of times an element is 0 in one vector and 1 in the other ($J_{01}, J_{10}$). Jaccard's coefficient is then calculated as follows: $\frac{J_{11,}}{J_{01}+J_{10}+J_{11}}$. The Jaccard similarity coefficients for pairwise comparison of discussion and familiarity networks are reported in Table 3 (see appendix); the numbers were calculated using UCINet software (Borgatti et al., 2002).

The Jaccard coefficient numbers are significant in more than fifty percent of the cells (shaded cells) in Table 3. However, S3 is the only experimental group for which the result are consistent with this paper's proposed hypotheses. In S3, Jaccard's coefficients are significant in all eight cells in support of Hypothesis 1. Furthermore, the Jaccard's similarity coefficient has an upward trend for all four discussions. This is consistent with Hypothesis 2, implying that the dyadic dynamic in the discussion networks mirrors the dyadic dynamic in the familiarity networks. The observation in S3 is, thus, fully consistent with our hypotheses, which points to potential control variables that have been omitted in the study design. Additionally, the Jaccard coefficient for D3 & F2 and D4 & F2 are higher and more significant than their counterparts for D1 & F2 and D2 & F2, hence we observe consistency between the evolution of connections in the discussion and familiarity networks. For the Jaccard's coefficients that are not statistically significant, we examined Hamming distance and the derived match coefficient. The match coefficient was significantly higher than Jaccard's coefficient in only one of the not-significant cells. A low Jaccard coefficient implies that there are not many corresponding dyads (cell ***ij***=1) in discussion and familiarity networks. When match coefficient is high despite the low Jaccard's coefficient, it implies that although there are not many corresponding dyads in the two networks, the non-existence of dyads (cell ***ij***=0) in the networks match at a high level.

**Mixed Dyad-Node Level Analyses**

To further understand the impact of students' face-to-face interactions on students' online interactions, a series of mixed dyad-node level analyses were performed. Mixed dyadic-nodal analyses started with calculating Jaccard similarity measures for students based on students' face-to-face interaction. The Jaccard similarity measures were then used to identify clusters within each course section. For each course section, clustering schemes with 2 to 5 clusters were examined, and the clustering scheme with the highest fit measure was chosen. In all course sections, 2 or 3 clusters yielded better fit measures. The above steps were performed for the two familiarity matrices in all six course sections. The cluster membership information for students in each course section (clusterIDs) were used as basis for three types of mixed nodal-dyadic analyses: structural block model, constant homophily, and variable homophily. These analyses can identify within-cluster commenting tendencies in online discussions for clusters identified in face-to-face interactions. Although mixed dyadic-nodal analyses did not yield any conclusive results in the current study, the analyses are essential for identifying segmentations within a class and for alleviating the impact of within-class segmentations on online discussions. If the analyses are run during the semester and after each discussion is completed, they can guide interventions to counter segmentations effects.

## 4. DISCUSSION

As explained in the previous section, the observations in a subset of course sections and discussions were consistent with this study's hypotheses. While the presented analyses are not conclusive, they provide some insights into how to examine the relationship between online and face-to-face interactions. To advance our understanding of how online and face-to-face interactions co-evolve and to establish and investigate the direction of causality, the theoretical framework of the study must be strengthened. Future theoretical and empirical studies based on this research project should try to shed light on the nature and dynamic of individuals' information processing habits when online and offline interactions are used in tandem (Walter 1992).

Also, patterns and dynamics of this relationship may be impacted by individual and environmental factors (e.g., average student's age) which should be taken into account using control variables. Such control variables, which would represent natural variances in classroom atmosphere and student characteristics, could explain some of the disparities among the reported comparison measures for the six course sections in the current data set. Due to the institutional limits of classroom research and concerns regarding coercion and privacy, this study's design did not include student characteristics. We also believe that including quality of the posts and comments as an additional variable in the model will help advance the understanding gained from this research study.

## 5. CONCLUSIONS

In this paper, we discussed the setup, analysis, and preliminary results of an exploratory study to examine the links between online and face-to-face interactions among students. The results suggest an individual's tendency for online interaction with people who are more connected with her/him in face-to-face settings. Online interaction with connected others could therefore limit depth and breadth of peer-learning in courses. Network-level, node-level, and dyadic analyses in this study were mostly consistent with this study's hypotheses that structure and evolution of online interactions mirror those of face-to-face settings.

The implication for educators is that discussion dynamics should be observed and discussion rules and instructions should be evolved throughout the semester to address observed undesirable patterns. Instruction rules should strive to alleviate observed segmentations in face-to-face settings and encourage students' open conversation beyond the acquaintance links with peers in class. For instance, to avoid dominance of a few students in attracting comments, educators can require students to comment on a pre-defined number of peers (as opposed to their chosen subset of peers) throughout the semester. If higher levels of reciprocity are observed (but not desired), instruction rules can limit the number of times a student can engage in debate-type conversations. Conversely, if a debate-type online conversation is desired, instruction rules can guide the depth of discussion threads and encourage involvement of more students in a single discussion thread. It is essential that instructions and rules evolve as students' face-to-face and online interactions evolve during the semester.

Future studies should be conducted to help gain a deeper understanding of how students interact within a specific thread, and to what extent the characteristics of the interactions (e.g., length of thread, timing of responses, and reciprocity within a thread) are associated with the status of the student who initiated the thread. Within-thread patterns of interaction can also provide insights regarding the extent to which a student's familiarity with another student is associated with his/her interactions with a third student (e.g., author of an original post). Future studies could further examine how student involvement in online discussions correlates with student performance in the course, as measured based on exam or assignment grades.

A deeper understanding of discussion dynamics in the virtual classroom can help guide the design of more effective course-related discussions that overcome familiarity fault-lines, and ultimately advance peer-learning. We hope to further contribute to the research stream of knowledge sharing and integration behavior in groups and the role of familiarity.

## 5. REFERENCES

Borgatti, S. P., Everett M. G., & Freeman L.C. (2002). Ucinet for Windows: Software for Social Network Analysis. Analytic Technologies, Harvard/MA.

De Vreede, G. J., Briggs R. O., van Duin R., & Enserink B. (2000). Athletics in Electronic Brainstorming: Asynchronous Electronic Brainstorming in Very Large Groups, in: J. F. Nunamaker, & R. H. Sprague (Eds.). *Proceedings of the 33rd Hawaiian International Conference on Systems Sciences*, IEEE Computer Society Press.

Gasson, S., & Waters J. (2011). Using A Grounded Theory Approach to Study Online Collaboration Behaviors. *European Journal of Information Systems*, 1-24 doi:10.1057/ejis.2011.24.

Gruenfeld, D. H., & Hollingshead A.B. (1993). Socio-Cognition in Work Groups – The Evolution of Group Integrative Complexity and Its Relations to Task-Performance. *Small Group Research, 24*(3), 383-405.

Gruenfeld, D. H., Mannix E. A., Williams K. Y., & Neale M. A. (1996). Group Composition and Decision Making: How Member Familiarity and Information Distribution Affect Process and Performance. *Organizational Behavior and Human Decision Processes, 67*(1), 1-15.

Goodman, P. S., & Leyden D. P. (1991). Familiarity and group productivity. *Journal of Applied Psychology, 76*, 578–586.

Homan, A. C., Van Knippenberg D., Van Kleef G. A., & De Dreu C. K. W. (2007). Bridging Faultlines by Valuing Diversity: Diversity Beliefs, Information Elaboration, and Performance in Diverse Work Groups. *Journal of Applied Psychology, 92*(5), 1189-1199.

Jaccard, P. (1912). The Distribution of the Flora in the Alpine Zone. *New Phytologist*, (11), 37–50, doi:10.1111/j.1469-8137.1912.tb05611.x.

Javadi, E., Gebauer, J., & Mahoney, J. (2013). The Impact of User Interface Design on Idea Integration in Electronic Brain-storming: An Attention-Based View. *Journal of the Association for Information Systems, 14*(1), 1-22.

Waters, J., & Gasson, S. (2006). Social Engagement in an Online Community of Inquiry. 27th International Conference on Information Systems (ICIS), Milwaukee WI.

Waters, J., & Gasson, S. (2012). Using Asynchronous Discussion Boards to Teach IS: Reflections from Practice. Proceedings of the 32nd International Conference on Information Systems (ICIS), Orlando, Florida, December 2012.

Walther, J. B. (1992). Interpersonal Effects in Computer-Mediated Interaction: A Relational Perspective. *Communication Research*, 19 (1), 52–90

 

## Appendix

**Table 1: Correlation among In-Degree Measures for Familiarity and Discussion Networks**

| Correlations | S1 N=26 | | S2 N=19 | | S3 N=29 | | S4 N=29 | | S5 N=21 | | S6 N=17 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | F1 | F2 | F1 | F2 | F1 | F2 | F1 | F2 | F1 | F2 | F1 | F2 |
| D1 | .390 | .288 | -.134 | -.014 | .239 | .406 | .205 | .195 | .225 | .309 | -.275 | -.310 |
| D2 | .354 | .132 | -.103 | .045 | .364 | .460 | .022 | -.195 | .096 | .336 | .151 | .255 |
| D3 | .381 | .336 | .324 | .221 | .208 | .489 | .093 | .207 | .076 | .481 | .306 | .091 |
| D4 | .326 | .494 | -.024 | -.057 | .036 | .364 | .348 | .372 | .444 | .044 | .198 | .265 |
| Correlation between F1 & F2 | .757 | | .374 | | .718 | | .309 | | .482 | | .624 | |

**Table 2: Correlation among Reciprocity in Discussion Network and Degree Centrality in Familiarity Network**

| Correlations | S1 N=26 | | S2 N=19 | | S3 N=29 | | S4 N=29 | | S5 N=21 | | S6 N=17 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | F1 | F2 | F1 | F2 | F1 | F2 | F1 | F2 | F1 | F2 | F1 | F2 |
| D1 | .396 | .133 | -.220 | .434 | .336 | .060 | -.360 | -.322 | .396 | .133 | -.079 | .453 |
| D2 | .502 | .243 | -.119 | -.167 | .073 | .481 | -.475 | -.202 | .502 | .243 | -.128 | .481 |
| D3 | .343 | -.002 | .312 | .287 | .252 | .398 | .149 | .143 | .343 | -.002 | .005 | .083 |
| D4 | .550 | .329 | .070 | .268 | -.137 | .376 | .124 | -.018 | .550 | .329 | -.190 | .238 |

**Table 3: Jaccard Coefficient to Measure Similarity among Discussions (D1-D4) and Familiarity Networks (F1, F2) for Course Sections S1 to S6**

| Jaccard Coefficient | S1 N=26 | | S2 N=19 | | S3 N=29 | | S4 N=29 | | S5 N=21 | | S6 N=17 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | F1 | F2 | F1 | F2 | F1 | F2 | F1 | F2 | F1 | F2 | F1 | F2 |
| D1 | 0.14* | 0.42 | 0.1 | 0.38 | 0.1* | 0.12* | 0.05 ***0.83*** | 0.12* | 0.19*** | 0.21*** | 0.14 | 0.58 |
| D2 | 0.13* | 0.39 | 0.14 | 0.47 | 0.16* | 0.35* | 0.07 | 0.37* | 0.27** | 0.64** | 0.14 | 0.58 |
| D3 | 0.14* | 0.5** | 0.1 | 0.37 | 0.16* | 0.37** | 0.05 | 0.31 | 0.21* | 0.62** | 0.29*** | 0.64 (p=0.07) |
| D4 | 0.17*** | 0.48** | 0.11 | 0.44 | 0.16* | 0.43*** | 0.1 | 0.4** | 0.26** | 0.6* | 0.18* | 0.59 |
| (F1 & F2) | 0.21*** | | 0.24*** | | 0.39*** | | 0.19*** | | 0.3*** | | 0.22*** | |
| *:<0.05 **: <0.01 ***: <0.001 | | | | | | | | | | | | |