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Understanding Students' Online Interaction: Analysis of Discussion Board Postings

Liyan Song and Scot W. McNary
Towson University

Abstract

The purpose of this paper was to report on the findings of a study examining students' online interaction patterns. The context of the study was a graduate online class delivered via Blackboard®. The primary data for the study came from students' discussion board postings, online learning journals, and course grades. Various data analysis methods such as descriptive and regression analyses were utilized to examine students' evolving interaction patterns and different interaction patterns among students in the same class. Results of the study indicated that there was considerable variability in students' postings. Students' postings were found mostly heterogeneous across students and across modules. The study suggested no correlation between the number of posts and students' success.

The number of online courses continues to grow in higher education (Allen & Seaman, 2006). One area that has been identified as an important factor affecting students' learning experiences in online learning environments is student interaction. Interaction in learning settings is a necessary and fundamental process for knowledge acquisition and cognitive development (Barker, 1994), and it has long been a focus of research for instructional designers (Hannafin, 1989). Online technologies such as asynchronous discussion forums provide the opportunity for learners to engage in social interaction by reading and responding to peers' and instructors' postings (Gallini & Barron, 2002); however, a review of the literature by Tallent-Runnels et al. (2006) found that the depth of such interaction or discussion is not equivalent to traditional face-to-face class sessions. The nature and depth of students' interaction in online environments is different from that of face-to-face classrooms (Kearsley, 2000). Whereas students in physical classrooms can interact face to face or outside of class, students in online courses may only interact with classmates through computer mediated communication (CMC) such as email, chat rooms, or discussion boards. Although asynchronous technology may allow students to compare progress with others, explore topics, and reflect more deeply (Johnson & Aragon, 2003), other students must share their own responses to realize the potential of online communication (Lapadat, 2002). Since online learning requires a higher level of student interdependence (Palloff & Pratt, 1999) and students must navigate time and space displacements (Bannan-Ritland, 2003), maintaining online interaction is a challenging task.

Understanding students' online interaction is important because interaction influences the quality of online learning (Trentin, 2000). According to Flottemesch's review (2000), students tend to judge the quality of distance education based on their perceived interaction in the distance education course. In addition, interactions among students in online classes can help motivate them to commit to learning (Gabriel, 2004; Rovai & Barnum, 2003). Students are motivated to be a part of the interaction and to contribute to the online interaction (e.g., online discussion) because it helps them to work collaboratively online with their peers (Gabriel, 2004; Song & Hill, 2009). To help facilitate students' online interaction for effective learning, it is important that we understand its unique characteristics.

Previous attempts to understand online interaction have been focused on the definition and description of online interaction (e.g., Moore, 1989; Hillman, Willis, & Gunawardena, 1994; Sutton, 2001). For example, Moore (1989) defined interaction in distance education into three types: learner-content, learner-instruction, and learner-learner. This definition has served as an important framework for scholars to understand students' interaction in distance education. With the advancement of technology and increasing complexity in distance education, Moore's classic interaction definition was expanded and additional types were added: learner-interface interaction (Hillman, Willis, & Gunawardena, 1994) and vicarious interaction (Sutton, 2001). Sutton (2001) stated that students in online environment can learn through vicarious interaction, which is to observe and actively process interactions which take place between others. More recently, Chapman, Ramondt, and Smiley (2005) have proposed a taxonomy of online interactions among students, which vary on dimensions of understanding (surface vs. deep), and experience of community ("I" vs. "we"). Several other content analysis systems exist (for a review see DeWever, Schellens, Valcke & Van Keer, 2005), but virtually all attempt to identify both cognitive and social features of online interaction. Evidence of student cognition among online discussions may facilitate assessment of learning and instruction, but social interaction is the most important element in designing online learning (Milheim, 1996), and it determines the quality of online learning (Trentin, 2000). How and what kinds of social exchanges to code varies across the content analysis systems, but the DeWever et al. (2005) paper identified the centrality of social interaction across the 15 systems they reviewed.

Although some research has shown that the number of online exchanges students initiate is positively related to course outcomes (Cook & German, 2009; Kay, 2006; Ramos and Yudko, 2008), little is known about the relationships between specific kinds of communication and student learning. In studying online learning success, Swan (2002) identified that the student-instructor interaction and student-student interaction positively influenced students' success. Swan (2002) further explained that the discussion among students contributed to students' success, implying the importance of the quality of student-student interaction in online discussion. Further differentiation of the social functions online posts communicate may yield additional insights about online discussions, and the association between post types and course performance.

Soller (2001) described a taxonomy of conversation behaviors, which she used to distinguish effective from ineffective contributions to real-time online collaborative problem solving. Soller's Collaborative Learning Conversation Skill Taxonomy (CLCST) illustrates the conversation skills that are most often exhibited in collaborative learning. There are three levels of those conversation skills, ranging from the general to the specific. The highest, most general level (level 3) includes three types of conversation skills: *Creative Conflict*, *Active Learning*, and *Conversation*. Each of these three skills is further broken down into corresponding sub-skills at Level 2. Creative Conflict includes two Level 2 behaviors: *Mediate* and *Argue*. Active Learning subsumes three level 2 behaviors: *Motivate*, *Inform*, and *Suggest*. Conversation includes *Acknowledge*, *Maintenance*, and *Task* related behaviors. Level 2 behaviors are further articulated into 36 Level 1 behaviors (See Table 1 for a complete list of the skills).

Table 1.
Modified Soller's Taxonomy (adapted from Soller's [2001] collaborative learning skills taxonomy)

Level 3 Codes	Level 2 Codes	Level 1 Codes
Creative Conflict	Mediate	Teacher mediation
	Argue	Agree
		Alternative
		Conciliate
		Disagree
		Doubt
		Exception
		Infer
		Suppose
Active Learning	Motivate	Encourage
		Reinforce
	Inform	Assert
		Elaborate-Inform
		Explain/Clarify-inform
		Justify
		Lead
		Resources
		Suggest
		Assert
	Request	Clarification
		Elaboration
		Illustration
		Information-Request
		Justification
		Opinion-Request
Conversation	Acknowledge	Accept/Confirm
		Appreciation
		Reject
	Maintenance	Apologize
		Attention
		Listening
		Request Confirmation
		Suggest action
	Task	Coordinate group process
		Focus change
		Present
		Summarize information
		End participation

The theoretical basis for the CLCST can be found in the peer group learning literature in which inter-dependence, accountability, promotive interaction, social skill, and group processing are necessary ingredients of a successful learning group (Johnson & Johnson, 2005). Each of the skills reflect one or more of those ingredients; for example, Motivate encodes behaviors that acknowledge and reinforce classmates' actions (promotive interaction), and Inform exemplifies accountability in which an individual's learning is shared with the group.

Soller's (2001) research indicated that successful online problem solving, mediated by specific exchanges of conversational acts, was associated with better learning performance among effective problem solving groups. However, her research was restricted to short-term projects, used highly structured online interactions (prompts), and consisted of students who knew both the topic and each other through face to face contact prior to the course. It is unknown to what degree this taxonomy 1) generalizes to sequences of unstructured interactions that transpire over the course of a semester among students who may not know each other or the topic well, and 2) adequately characterizes interactions about individual (vs. collaborative) projects.

On balance, the importance of online interaction to students' learning experience seems clear; however, a sound theoretical foundation for determining what good quality interaction is and how it affects students' learning success is lacking (DeWever et al., 2005). To accomplish this, it is important that we have a good understanding of students' online interaction: the patterns and functions of students' posts, the functions of the posts and the association of posts with student learning. In addition, the impact of instructional design on students' online interaction is an area that needs more research.

Methods

The purpose of this study was to examine students' online interaction patterns and to examine the relationship between students' online interactions and their course performance in a graduate online course. In this section, we provide descriptions for the context of the study, the participants, research questions, data coding, and data analysis.

Context and Participants

The context of the study was a graduate level online course that was delivered via Blackboard®. The course consisted of seven modules. For each module, students were asked to complete topic related readings and participate in asynchronous online discussion in the main discussion board in the course Blackboard site. At the end of each module, students were asked to write a learning journal to reflect and evaluate their learning experience for that module. Students' learning journals were posted in the private group page that was set for each group to which only the student and the instructors had access. Students received a grade for each module and the final project. The primary means of communication among students and the instructor took place in the course Blackboard site. Email was used when students had specific individual questions for the instructor, but was not considered in this study.

There were 18 students in the class, and 83% were female (N = 15). Among the participants, sixteen were Caucasian and two were African American. Two were doctoral students (11%), and the rest were master's level graduate students. One female master's graduate student withdrew from the class; however, her postings were retained in the study.

Research Questions

The study investigated the following research questions:

1. How much variability in type of discussion board post existed among the students of this course?
2. How did the types of posts change over time?
3. How did students differ from one another in amount, type, and pattern of posts over time?
4. What was the relationship between discussion board posts and course grades?

Data and Coding

Students' discussion-board postings, their learning journals, and their grades (module grades, final project grades, and course grades) were the data sources for this study. Three of the seven modules were selected to analyze students' online interaction patterns over time: Module 1, Module 3, and Module 7. We selected those three modules because they occurred at the beginning, middle, and end of the semester. Module 1 was a two-week long module. For the first week of the module, the class was divided into two groups (Group A and Group B). Students from each group participated in their own specific discussion forum to discuss the same topics (definitions and characteristics of distance education). Discussion postings from Group A discussion forum were collected as data set 1a, postings from Group B forum were collected as data set 1b. During the second week of Module 1, students participated in the whole class discussion (share and exchange ideas on each other's definitions and characteristics) in the main discussion forum and postings from the whole class discussion were collected as data set 1c. Module 3 was a two-week module (on teaching and learning philosophies), Module 7 was a one-week module (on emerging technologies), and both of them involved the whole class discussion.

The function of each discussion board post (N =1371) was coded by the authors using the CLCST (Soller, 2001). The authors coded each post first individually and then jointly, with all discrepancies resolved by mutual agreement. One of the authors was an instructor for the course that was studied, who had taught this online course three times, which helped enhance the validity of coding. Four new codes ("Pardon", "That's funny", "Present", and "Resources") were added to the CLCST, as they appeared distinct enough to require new categories, producing a total of 40 Level 1 codes.

Analysis

The unit of analysis was a student's post, which had several attributes: date, author, thread title, post title, code, and page number. Two research assistants entered the data into a spreadsheet. Two sets of input data were compared and keying errors were resolved by reference to the original data sources.

Descriptive statistics including means, SD, medians, and ranges were used to describe counts of the different kinds of posts for Research Question 1. For Research Question 2, we conducted analyses of post type over time using Poisson regression, with module length in days as an exposure variable to control for differences in lengths of modules. Differences between types of codes and modules were tested for significance to see whether some codes were used more frequently than others, and if different modules contained different frequencies of posts. A separate analysis was conducted for Level 1, Level 2, and Level 3 post types. For Research Question 3, a visual inspection of figures provided showing students' change in number of posts by type over time. Finally, for Research Question 4, Pearson Product Moment correlation coefficients were calculated to represent the association between post type and class performance. For Research Questions 2 and 4, in which significance testing was done, a significance level of 0.05 was used to determine statistical significance.

Results

Research Question 1: How much variability in type of discussion board post existed between the students of this course?

A total of 40 Level 1 codes (36 from the CLCST and 4 new codes added by the authors) were used. There was considerable variability in the frequency of code use (Mean = 35.1, SD = 63.7), and the distribution of the frequencies was highly positively skewed (Median = 8, Minimum = 1, Maximum = 313). The most frequently used codes were "Inform-Suggest" (n = 313) and "Inform Explain/Clarify" (n = 205). Students also demonstrated considerable variability in posting behavior, ranging from 7 to 169, with an average of 65.1 posts per person (SD = 33.6, Median = 64).

Research Question 2: How did the types of posts change over time?

Level 1 codes. We only used post types with Level 1 codes that were used more than 15 times during the modules in this analysis. The rate of posts per day by module is shown in Table 2. The effect of module was statistically significant, suggesting the number of posts varied over time, $X^2(3) = 125.7$, $p < .001$ (see Table 2). This effect was due to the decreased number of posts in Module 3 relative to Module 1ab, B = -0.73, SE = 0.08, Z = -8.71, p < 0.001; Module 1c, B = -0.77, SE = 0.19, Z = -8.85, p < 0.001; and Module 7, B = -0.80, SE = 0.09, Z = 9.25, p < 0.001. Put another way, the number of all posts, regardless of type, in Module 3 was fewer than half (48%, 46%, and 45% respectively) of Modules 1ab, 1c, and 7. Type of post used was also statistically significant, $X^2(15) = 207.9$, $p < .001$ (see Table 2). This effect was due to the increased frequency of Suggest, Explain/Clarify, and Agree posts relative to others (see Table 3). Significant differences were also found across students.

Table 2.
Analysis of Deviance of Student, Code Type, and Module Effects on Post Rate

		Level 1			*Level 2*			*Level 3*	
Factor	Df	X^2	p	df	X^2	P	df	X^2	p
Student	20	57.0	<0.001	20	16.2	0.70	20	35.6	0.02
Post Type	15	207.9	<0.001	6	30.8	<0.001	2	49.1	<0.001
Module	3	125.7	<0.001	3	57.8	<0.001	3	80.3	<0.001
Post Type × Module			ns			ns	6	13.5	0.04

Note: ns = Not statistically significant. The test statistic for factors is X^2 on the deviance for each factor, used in Poisson regression.

Table 3.
Mean Number of Posts per Day by Type of Post and Module

	Module 1ab		Module 1c		Module 3		Module 7	
	M	SD	M	SD	M	SD	M	SD
Level 1								
Accept/Confirm	0.30	0.11	NA	NA	0.07	0.00	0.18	0.07
Agree	0.34	0.20	0.55	0.37	0.19	0.12	0.29	0.19
Appreciation	0.28	0.13	0.24	0.12	0.10	0.08	0.23	0.10
Coordinate group process	0.29	0.23	0.14	NA	0.29	NA	1.43	NA
Disagree	0.14	0.00	0.18	0.07	0.09	0.04	0.14	0.00

Doubt	0.14	0.00	0.18	0.07	0.07	0.00	0.14	0.00
Encourage	0.24	0.14	0.25	0.15	0.12	0.09	0.29	0.20
Exception (propose exception)	0.20	0.14	0.14	0.00	0.12	0.07	0.16	0.05
Explain/Clarify-inform	0.32	0.25	0.53	0.43	0.20	0.12	0.41	0.24
Request information-Request	0.16	0.05	0.20	0.08	0.07	0.00	0.27	0.25
Request opinion	0.27	0.24	0.21	0.13	0.15	0.12	0.35	0.38
Pardon	0.29	0.15	0.24	0.11	0.07	NA	0.27	0.14
Resources	0.14	0.00	0.21	0.14	0.21	0.14	0.31	0.15
Suggest	0.64	0.25	0.52	0.34	0.28	0.20	0.73	0.35
Suggest action	0.17	0.06	0.14	NA	NA	NA	0.14	0.00
Summarize information	0.26	0.17	0.14	0.00	0.13	0.08	0.21	0.10
Level 2								
Acknowledge	0.25	0.06	0.14	0.00	0.08	0.02	0.21	0.10
Argue	0.24	0.11	0.34	0.16	0.15	0.06	0.28	0.10
Inform	0.33	0.09	0.28	0.09	0.15	0.04	0.29	0.05
Maintenance	0.26	0.12	0.17	0.06	0.13	0.07	0.20	0.09
Motivate	0.16	0.07	0.18	0.06	0.08	0.02	0.14	0.00
Request	0.21	0.07	0.18	0.07	0.09	0.04	0.27	0.15
Task	0.23	0.10	0.20	0.11	0.09	0.03	0.19	0.10
Acknowledge	0.25	0.06	0.14	0.00	0.08	0.02	0.21	0.10
Level 3								
Active Learning	0.61	0.17	0.53	0.20	0.27	0.10	0.55	0.22
Conversation	0.56	0.23	0.33	0.19	0.13	0.10	0.45	0.25
Creative Conflict	0.24	0.11	0.34	0.16	0.15	0.06	0.28	0.10

Note: NA=insufficient observations to calculate.

Figure 1 displays students' rate of posts per day for highly used categories across module. Each line plot represents a student's posting history and each panel of the graph represents a particular type of post. The diversity of trajectories shown indicates student variability in posting habits across modules, and differences among panels show how some post types (e.g., Agree) were used more frequently than others (e.g., Disagree). Finally, the general pattern of peaks shows which module tended to elicit particular kinds of posts. Agree posts occurred more frequently during Module 1ab whereas Suggest posts occurred more frequently during Module 7.

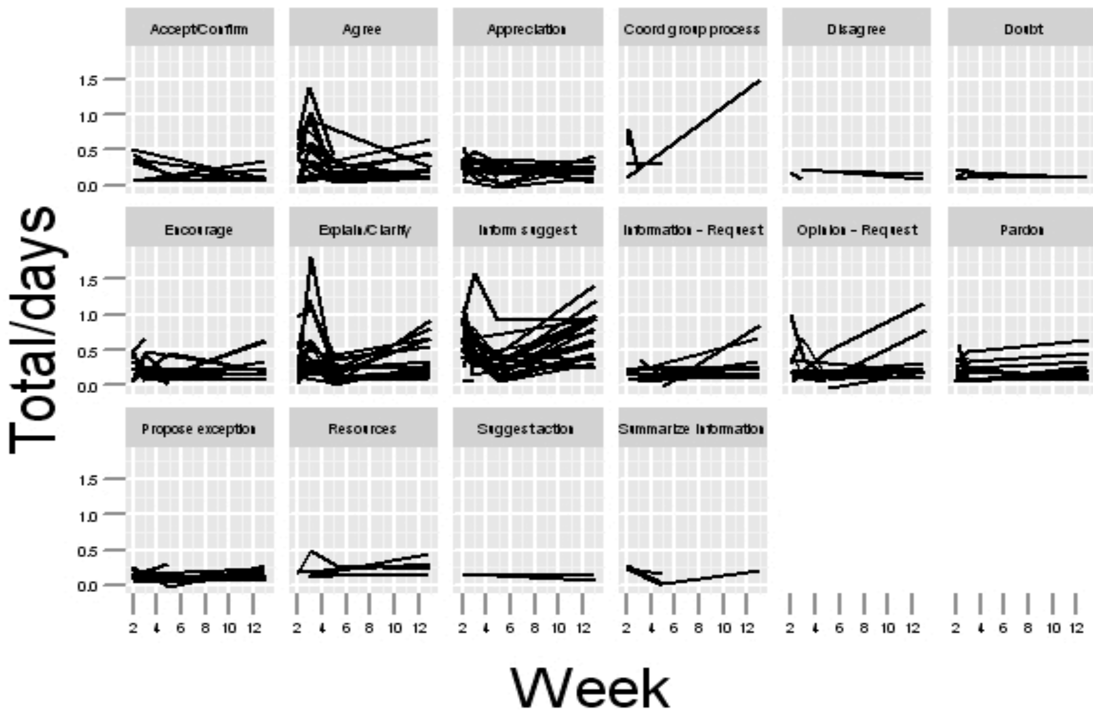

Figure 1. Rates of Level 1 Codes by Module. Only the fifteen most frequently used Level 1 codes are displayed (Accept/Confirm, Agree, Appreciation, Coordinate group process, Disagree, Doubt, Encourage, Propose exception, Explain/Clarify, Request information, Request opinion, Pardon, Sharing resources, Suggest-Inform, Suggest action, Summarize information. Total/days=average number of posts per day for module.

Level 2 codes. The significant effect for module implied that the mean number of posts varied over time, X^2 (3) = 57.0; p < .001 (see Table 2). This effect was due to the decreased number of posts in Module 3 relative to Module 1ab, B = -0.77, SE = 0.11, Z = -6.716, p < 0.001; Module 1c, B = -0.66, SE = 0.12, Z =-5.46, p < 0.001, and Module 7, B = -0.69 SE = 0.12, Z = 5.72, p < 0.001. For the Level 1 codes, there were about half as many posts made in Module 3 as the three others (46%, 52% and 50% for Modules 1ab, 1c, and 7, respectively).

Differences in the number of different Level 2 post types were found, X^2 (6) = 30.8; p < .001 (seeTable 2). Specifically, students were more likely to make Inform posts than Acknowledge (B = 0.43, SE = 0.14, Z = 2.99, p = 0.04) or Motivate posts (B = 0.66, SE = 0.15, Z =4.284, p < 0.001) and more Argue than Motivate posts (B = .61, SE = 0.16, Z = 3.90, p = 0.002). Put another way, on average students made *exp*(0.43) = 1.54 times as many Inform as Acknowledge posts, *exp*(0.66) = 1.93 times as many Inform as Motivate posts, and *exp*(0.61) = 1.84 times as many Argue as Motivate posts over all four modules (see Table 3; Figure 2).

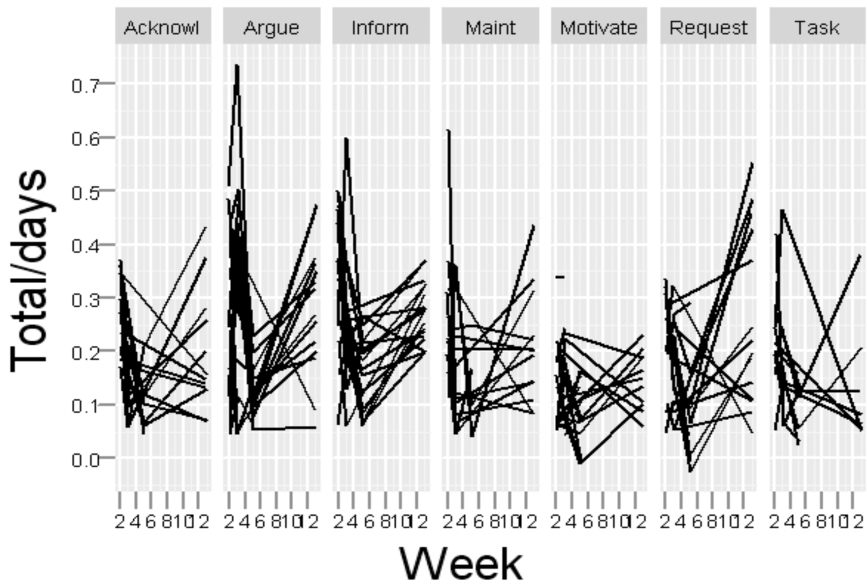

Figure 2. Rates of Level 2 Codes by Module. Acknowl = Acknowledge. Maint = Maintenance. Total/days=average number of posts per day.

Level 3 codes. Just as with Level 1 and Level 2 codes, there was a significant effect of module and type of post. However, the interaction between module and type of post was also statistically significant, $X^2(6) = 13.5$, $p = 0.04$ (see Table 2), suggesting differences in the rate of post type over modules. Visual inspection of plots revealed that Active Learning and Conversation posts were most frequent in Module 1ab and Module 7, but decreased substantially in Module 3. In contrast, Creative Conflict posts peaked later in Module 1c and also in Module 7 (see Table 3; Figure 3). As with Level 1 codes, but not Level 2, statistically significant differences were found across students, supporting the interpretation of student heterogeneity in rate of posting (see Figure 3).

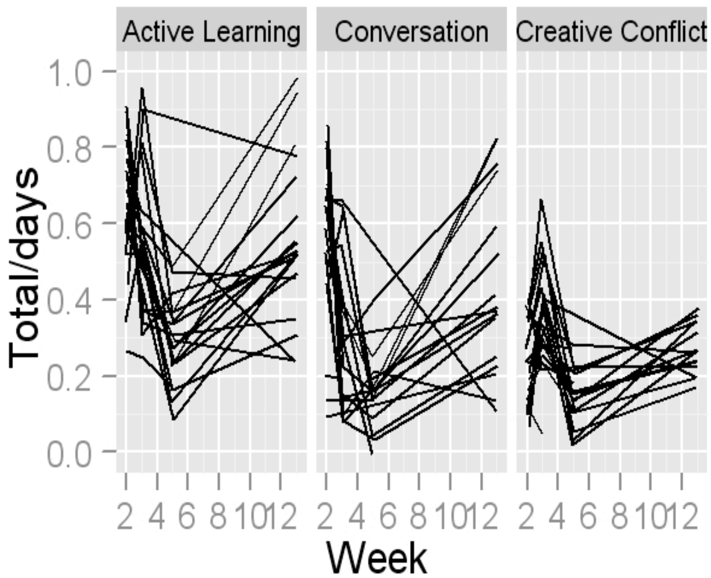

Figure 3. Rates of Level 3 Codes by Module. Total/days=average number of posts per day.

Research Question 3: How did students differ from one another in amount, type, and pattern of posts over time?

A visual inspection of the most frequently used post types by module for each student suggests the most frequently used post types (Suggest, Explain/Clarify, Agree; Figure 1) showed considerable heterogeneity across students. Some students maintained a constant rate in their use of these kinds of posts, at high or low levels, but other students were much more variable. In contrast, the other post types showed less variability across time or student. Figures 2 and 3 show similar degrees of student variability for Level 2 and 3 post types, respectively. Tests of significance conducted for the effect of Student showed statistically significant differences between students for Levels 1 and 3, but not Level 2 (see Table 2).

Due to the fact that most of the participants in our study were female (15 out of 18), gender differences were not examined in our study. It would be helpful to see in future studies how students of different gender differ in their discussion board posts.

Research Question 4: What was the relationship between discussion board posts and course grades?

Correlations between the number of posts and course grades were calculated and revealed that total number of posts correlated moderately with course grades; correlation coefficients (*r*) between total number of posts and grades on assessments at the end of modules 1, 3, 7, and the final grade were 0.17, 0.25, 0.43, 0.19, respectively. Interestingly, the strongest correlation was between the Module 7 grade and total number of posts, but not with final course grade.

Discussions and Implications

The findings from the study suggest a few implications for the taxonomy instrument and for online course design. Those implications are discussed in the following section.

Course Design vs. Students' Interaction

The findings from the study seem to suggest a relationship between course design and the types of students' interaction. The most frequently observed types of postings were "Inform-Suggest" and "Explain/Clarify". These were the types of interactions that instructors expected from module discussion assignments. The course was discussion-oriented by design and students were expected to improve their understanding of various topics through asynchronous discussion with their peers and the instructors. Leading discussion questions were provided in each module that asked students to share and exchange their ideas on various topics. The fact that there were more 'Inform-Suggest" and "Explain/Clarify" posts in the discussion seems to align with the course design.

In addition, the findings on how students' posts changed over time seem to provide further evidence for a relationship between course design and the types of students' interactions. For example, more Conversation (specifically Accept/Confirm) and Active Learning (specifically Suggest Information) posts occurred in week 1 during the module 1ab when students broke into subgroups to generate group consensus (on the definitions and characteristics of distance education). Naturally, the discussion assignments led students to offer suggestions and acknowledgement of contributions from classmates. The following week in module 1c when both groups came together for the whole class discussion, groups shared their consensus process with the rest of the class. During this week of the module students made more Creative Conflict (e.g., Argue-Agree) and Active Learning (e.g., Explain/Clarify) posts, consistent with the instructors' expectations for students' sharing of work in a class discussion.

The students in this course seemed to have followed the course guidelines when participating online discussions. However, the design of the course itself does not necessarily guarantee the success of discussions. It takes intrinsic motivation from the students (Song & Hill, 2009) and the effective facilitation and guidance from the instructors to produce successful online learning because it is difficult to get students to begin interaction, then once started, it can sometimes go off topic (Hawkes & Dennis, 2003). Studies on the interaction among course design, students' motivation, and instructor's facilitation may help produce a more comprehensive understanding of successful asynchronous online learning.

CLCST for Asynchronous Collaborative Learning Environments

The use of the CLCST (Soller, 2001) in our study yielded observations consistent with some of our expectations, suggesting this taxonomy has utility in categorizing online discussion board posts. Some of our expectations were not borne out, however. Some types of posts demonstrated little change during the course (Disagree, Doubt, Suggest action) and others were rarely observed (Conciliate, Justify, Humor, Present). It is unclear why this was the case; perhaps we had insufficient data. We restricted our sample of discussion board posts to only three of seven modules in a single class. Or perhaps the CLCST needs further refinement for this kind of online interaction, a setting for which it was not originally developed. We also do not know to what degree these findings generalize to different samples of students taking different courses.

Nevertheless, the findings are encouraging in terms of the utility of the CLCST to code online discussion postings.

Number of Posts vs. Students' Success

The study also investigated the relationship between the number of posts and students' course grades. The results did not show a strong correlation between these variables. This is in contrast to the findings by some researchers (Cook & German, 2009; Kay, 2006; Ramos and Yudko, 2008) that suggested that number of posts classroom performance were very strongly related. We suspect we did not find this association because this was a graduate level course and there was little variation in students' grades. It may also be that it is the quality rather than the volume of students' posts that is strongly associated with course performance. Whereas the CLCST may be a useful classifier of post function, it does not provide information on the quality of each post. Had we been able to assess the quality of the posts and utilize a finer-grained measure of course performance, a stronger relationship between the types of posts and students' performance in online classes may have emerged.

Conclusions

Overall, this study shows some useful findings for people to understand students' online interaction patterns. It provides a new way to code threaded discussion postings and several innovative analysis approaches. The results of the study suggest that Soller's instrument is a useful tool in coding online discussion postings. We believe future studies are warranted to assess students' online postings, online learning success in discussion-oriented graduate online courses, and to understand the relationship between students' postings and their learning.

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