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EXAMINING THE EFFECTS OF DISCUSSION STRATEGIES AND LEARNER

INTERACTIONS ON PERFORMANCE IN ONLINE INTRODUCTORY

MATHEMATICS COURSES: AN APPLICATION

OF LEARNING ANALYTICS

by

Ji Eun Lee

A dissertation submitted in partial fulfillment
of the requirements for the degree

of

DOCTOR OF PHILOSOPHY

in

Instructional Technology & Learning Sciences

Approved:

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Logan, Utah

2019

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ABSTRACT

Examining the Effects of Discussion Strategies and Learner Interactions on Performance in Online Introductory Mathematics Courses: An Application of Learning Analytics

by

Ji Eun Lee, Doctor of Philosophy

Utah State University, 2019

Major Professor: Mimi Recker, Ph.D.
Department: Instructional Technology and Learning Sciences

Asynchronous online discussion is one of the most widely used instructional methods in online learning environments. Previous studies have shown that the use of online discussions helped in improving not only learners' engagement but also an achievement. Thus, it can be used as one possible solution for improving student success in online mathematics courses. However, while many previous studies have demonstrated the effectiveness of using online discussions, the effective use of online discussions has been seldom studied in mathematics learning contexts.

This dissertation study explored: 1) instructors' use of discussion strategies that enhance meaningful learner interactions in online discussions and student performance, and 2) learners' interaction patterns in online discussions that lead to better student performance in online introductory mathematics courses. In particular, the study used a data-driven approach by applying a set of data mining techniques, such as a semi-automated content analysis, Classification and Regression Tree (CART) analysis,

Hierarchical Linear Modeling (HLM), to a large-scale dataset automatically collected by the Canvas Learning Management System (LMS) for five consecutive years at a public university in the U.S., which included 2,869 students enrolled in 72 courses.

First, the results of the CART analysis revealed that the courses that posted more open-ended prompts, evaluated students’ discussion messages posted by students, used focused discussion settings (i.e., allowing a single response and replies to that response), and provided more elaborated feedback had higher students final grades than those which did not. Second, the Kruskal Wallis H-tests showed the instructors’ use of discussion strategies (discussion structures) influenced the quantity (volume of discussion), the breadth (distribution of participation throughout the discussion), and the quality of learner interactions (levels of knowledge construction) in online discussions. Lastly, the results of the two-level HLM analysis revealed that the students’ messages related to allocentric elaboration (i.e., taking other peers’ contributions in argumentive or evaluative ways) and application (i.e., application of new knowledge) showed the highest predictive value for their course performance.

The findings from this study suggest that it is important to provide opportunities for learners to freely discuss course content, rather than creating a discussion task related to producing a correct answer, in introductory mathematics courses. Other findings reported in the study can also serve as guidance for instructors or instructional designers on how to design better online mathematics courses.

(127 pages)

PUBLIC ABSTRACT

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Ji Eun Lee

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ACKNOWLEDGMENTS

Foremost, I would like to express my sincere gratitude to my advisor, Dr. Mimi Recker, for her invaluable guidance, patience, and continuous encouragement during my doctoral studies. Without her support and excellent supervision, I could not have completed this long journey. She is truly the best mentor, researcher, and my role model.

I would like to extend my thanks to the members of my dissertation committee, Dr. Andy Walker, Dr. Jody Clarke-Midura, Dr. Daniel Coster, and Dr. Yong-Seog Kim, for all of their valuable suggestions, constructive feedback, and support to improve research. In addition, I wish to thank all the professors in ITLS department, in particular, Dr. Breanne Litts and Dr. Jina Kang, for the helpful advice and encouragement.

I am also extremely grateful to my amazing family, my parents, my sister, and brother, for always believing in me and encouraging me to pursue my dreams. I cannot thank you all enough for all the support and love.

Finally, I would like to thank my friends and fellow graduate students, who have been willing to hear me, help me and share laughter and tears with me throughout the years.

Ji Eun Lee

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GLOSSARY

Asynchronous Online Discussion (AOD) – an online text-based learning activity in which students are engaged in discussing a particular topic by interacting with an instructor or other peers (Darabi et al., 2013).

Classification and Regression Tree (CART) – one of the decision tree algorithms. It progressively segments samples into subgroups by identifying which variables (and in what order) best predict the outcome variable (Lemon et al., 2003)

Knowledge Discovery in Databases (KDD) Process – “the nontrivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data” (Fayyad, Piatetsky-Shapiro, & Smyth, 1996, p. 30).

Learner Interactions - defined as communication between one learner and other learners or instructors in collaborative or cooperative learning settings (Anderson, 2008; Moore, 1989).

Learning Analytics – “the measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs” (Siemens & Baker, 2012, p. 252).

LightSIDE – a text mining tool developed by researchers at Carnegie Mellon University for natural language processing (NLP). Based on the training data hand-coded by a human, the tool develops a classification model using machine learning algorithms (Mayfield, Adamson, & Rosé, 2013).

CHAPTER I

INTRODUCTION

Problem Statement

Mathematical skill is one of the core competencies for the 21st century (Dede, 2010; Partnership for 21st Century Learning, 2015). It is not only a foundation for all Science, Technology, Engineering, and Math (STEM) disciplines but also helps learners solve complex problems and make important connections to other fields (Chen & Soldner, 2013). A recent study found that mathematical ability also influences career success and accomplishments (Lubinski, Benbow, & Kell, 2014).

Challenges in College Mathematics

"Mathematics courses are the most significant barrier to degree completion" (Saxe & Braddy, 2015, p.28).

"The main impediment to graduation: freshman math" (Hacker, 2012).

Despite the importance of math skills, high failure rates in college math courses have become a growing concern in the United States (King, Mcintosh, & Bell-ellwanger, 2017). One report found that approximately 50% of U.S. college students do not pass college algebra courses with a grade of C or above (Saxe & Braddy, 2015). The negative experiences in math courses also affect degree completion. The result of a nation-wide study indicated that negative experiences in math courses, such as poor performance or withdrawal, were associated with not just leaving STEM majors, but also led to a higher

probability of dropping out of college (Chen & Soldner, 2013).

More seriously, while the number of students taking online courses is rapidly increasing, online math courses showed even worse results, with a 20% higher failure/withdrawal rates (62%) compared to face-to-face counterparts (43%) (Jaggars, Edgecombe, & Stacey, 2013).

Possible Solution

In online learning environments, one of the widely used instructional methods to enhance learners'engagement, presence, and achievement is *asynchronous online discussions*, a type of Computer-Supported Collaborative Learning (CSCL) (De Wever, Schellens, Valcke, & Van Keer, 2006; Hew, Cheung, & Ng, 2010; Ke & Xie, 2009; Wang, 2008). Asynchronous online discussions provide learners opportunities to construct ideas carefully, reflect on their thinking, as well as to share ideas and experiences with an instructor or other peers (Chen, Chiu, & Wang, 2012; Groth, 2008; Xie & Ke, 2011). Many previous studies have shown that using asynchronous online discussions had significant effects on increasing students' achievement (Bernard et al., 2009; Pettijohn, Terry, & Pettijohn, 2007), critical thinking skills (Maurino, 2007), and engagement (Salter & Conneely, 2015). In addition, for instructors, the use of asynchronous online discussions provides opportunities to monitor students' learning progress (Groth, 2008).

In mathematics education, it is also important to involve learning activities that develop students' mathematical thinking and communication skills to increase their mathematical understanding and success. The "Curriculum guide to majors in the

mathematical sciences" introduced by the Mathematical Association of America noted that "major programs should include activities designed to promote students' progress in learning to communicate mathematical ideas clearly and coherently both verbally and in writing to audiences of varying mathematical sophistication" (Schumacher, Siegel, & Zorn, 2015, p.10). A number of studies have also demonstrated that the use of online discussions have helped in decreasing math anxiety (Liu, 2008), the creation of correct and new ideas (Chen et al., 2012), and achievement outcomes (Sowell, 2009; Thomas, Li, Knott, & Li, 2008; Tunstall & Bossé, 2015).

However, the use of online discussions does not always lead to productive interactions or knowledge construction. Many studies reported that students often exhibited low participation rates and low levels of critical thinking or knowledge construction in online discussions (Ertmer, Sadaf, & Ertmer, 2011; Hew et al., 2010; Maurino, 2007; Stegmann, Wecker, Weinberger, & Fischer, 2012). Pratt and Back (2009) noted that "simply providing such environments is not necessarily enough to change students' mathematical practices, and that educators need to think carefully about the structures, tools and social rules that operate within them" (p. 129).

Indeed, several empirical studies have revealed that learners exhibited a higher level of engagement or performed better in *effectively designed and structured* online discussions (Borokhovski, Tamim, Bernard, Abrami, & Sokolovskaya, 2012; Darabi, Liang, Suryavanshi, & Yurekli, 2013; Salter & Conneely, 2015). Thus, it is important to offer well-designed and domain-specific support to engage learners in meaningful activities and discourse (Vogel, Kollar, Ufer, Reichersdorfer, Reiss, & Fischer, 2016).

Nonetheless, instructors seldom strategically implement online discussions that

are purposefully designed or structured (Darabi et al., 2013). In addition, in terms of research, several gaps were identified. First, although there have been numerous studies in CSCL, most of the studies tended to focus on students' behaviors or interactions, rather than instructor involvement (Maurino, 2007). Little research has investigated what design strategies, such as the design of activities or discussion tasks, lead to meaningful student interactions (Ke & Xie, 2009). Second, the effective use of online asynchronous discussions has seldom been studied in mathematics learning contexts although the implementation of online discussions has been less successful in mathematics learning contexts compared to other academic disciplines (Maurino, 2007; Nason & Woodruff, 2004),

Research Purpose and Questions

To address these challenges in research and practice, the aim of this study is twofold. The first is to explore what are the effective discussion strategies that enhance meaningful learner interactions in online discussions and achievement outcomes in online introductory mathematics courses. The second is to investigate learner behaviors and interaction patterns that lead to better learning outcomes. In particular, by using a data-driven approach and applying a set of data mining techniques, this study analyses large-scale data automatically collected by a Learning Management System (LMS) for five consecutive years at a university located in the western U.S.

The specific research questions are as follow:

For online introductory mathematics courses:

Research Question 1: What online discussion strategies are associated with positive student performance?

Research Question 2: To what extent do different structures designed into online discussions impact the kinds of learner interactions in online discussions?

Research Question 3: What types of learner interactions in online discussions are associated with positive student performance?

Dissertation Outline

This dissertation is structured as follows: Chapter II reviews the literature regarding the use of asynchronous online discussions in mathematics learning contexts, instructors' use of online discussion strategies, and learner interactions in online discussions. Chapter III describes the research methodology, including research context and sample, research design and procedures, measurement, data preprocessing process, and data analysis methods. Chapter IV reports the results corresponding to the three research questions: 1) instructors' use of online discussion strategies and course performance, 2) instructors' use of online discussion strategies and learner interactions in online discussions, and 3) learner interactions in online discussions and course performance. Lastly, Chapter V discusses the findings of the study and concludes with the contribution and implications of the work as well as limitations and recommendations for future research.

CHAPTER II

REVIEW OF LITERATURE

Theoretical Framework Underlying the Research Purpose

To examine the relationship between instructors' use of discussion strategies, learner interactions in online discussions, and learning outcomes, a research model was created based on Biggs's 3P model (Biggs, 1991). The 3P model explains the relationship between three *phases, presage, process*, and *product* (See Figure 1).

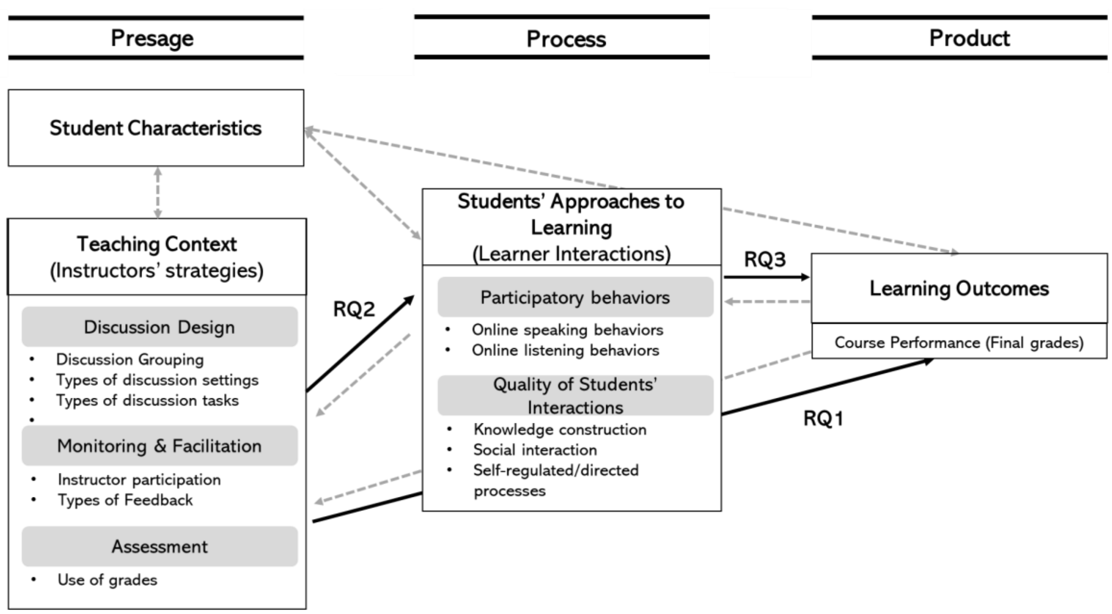

Figure 1. The research model adopted from Biggs' Presage-Process-Product (3P) model

The presage phase includes *student characteristics* such as prior knowledge, abilities, motivation, and *teaching context*, such as curriculum, course design, teaching methods, assessment. The process phase refers to students' approaches to learning; in

other words, the way students interpret the teaching contexts in compliance with their preconceptions, motivation, and the nature of learning tasks. The product phase refers to learning outcomes, final grades, as well as affective outcomes such as satisfaction.

The 3P model assumes that the four factors, student characteristics, teaching context, students' approaches to learning, and learning outcomes are interrelated and affect each other. Among the four factors, this proposed study focuses on the relationship between teaching context (instructors' use of discussion strategies), students' approaches to learning (learner interactions in online discussions) and learning outcomes (course performance).

Review of Relevant Empirical Studies

In this section, the existing literature on three topics was reviewed; 1) use of asynchronous online discussions in mathematics learning, 2) instructors' use of online discussion strategies, 3) learner interactions in online discussions. The researcher searched five databases: Education Source, ERIC via EBSCOhost, Professional Development Collection, PsycINFO via EBSCOhost, and Google scholar. Five criteria are considered for inclusion: the studies were published in the past ten years, published in peer-reviewed scholarly journals, conducted in higher education contexts, written in English, and had full text available. However, for some topics, doctoral dissertations, articles published in conference proceedings, and articles published after the year 2000 were also included due to the limited number of studies available.

Use of Asynchronous Online Discussions in Mathematics Learning

An asynchronous online discussion refers to an online text-based learning activity in which students are engaged in discussing a particular topic by interacting with an instructor or other peers (Darabi et al., 2013).

Although there is limited research investigating the use of online discussion in mathematics learning contexts (Loncar, Barrett, & Liu, 2014; Ozyurt & Ozyurt, 2011), a few studies found that the use of online discussion had positive influences on learning gains (Tunstall & Bossé, 2015), critical thinking skills (Seo, 2014), creation of correct, new ideas (Chen et al., 2012), and decreasing students' anxiety (Liu, 2008) in mathematics learning contexts.

Specifically, one study (Tunstall & Bossé, 2015) found that using online discussion with a design-based on problem-based learning (PBL) instructional approach led to statistically significant gains in students' mathematics performance. The study compared the students' learning gains in two different sections of college algebra courses, face-to-face, and online sections. The face-to-face section was a traditional lecture-based course, whereas the students in the online section were engaged in problem-based learning activities, such as discussing the application of mathematics content they had learned. The result indicated that the students in the online section showed significant learning gains in their quantitative literacy and reasoning performance, while the students in the face-to-face section did not.

Liu (2008)'s study showed that using online discussions had a significant positive impact on reducing pre-service teachers' anxiety toward teaching mathematics in introductory mathematics classes. The pre-service teachers participated in the online

discussion for eight weeks and discussed anxiety towards teaching mathematics. The instructor provided open-ended question prompts; for example, "Why do you think might be some of the reasons why some of us are anxious about our future teaching of mathematics?" (p. 622). The study compared the participants' level of anxiety before and after the discussion, and the results indicated that their level of anxiety significantly reduced at the post-measurement.

However, one study (Emig, 2009) found that the use of online discussion did not have significant impacts on learning outcomes. Similar to Liu (2008)'s study, the students in the intervention group discussed their math anxiety and personal experiences regarding studying college algebra on the online discussion boards. While the interview data revealed that the students perceived that online discussions helped reduce their anxiety, the quantitative results indicated there were no statistically significant differences in the students' math anxiety, course performance, and course retention between the intervention group and the control group.

Moreover, many studies reported challenges in using online discussions in math courses, such as students' superficial knowledge contributions and lack of group knowledge construction. For instance, Thomas et al. (2008) explored students' interaction patterns on online discussion boards in undergraduate mathematics courses. The researchers found that the students only focused on the discussion topics that directly affected their final grades, such as creating homework reports, whereas they neglected other topics that were not related to final grades. Similarly, Groth and Burgess (2009) also reported that the results of a content analysis revealed that most of the discussion messages posted by the participants lacked mathematical contents or knowledge.

Some researchers pointed out the reasons why it is more challenging to facilitate meaningful discourse or group knowledge constructions in mathematics learning contexts (Groth & Burgess, 2009; Nason & Woodruff, 2004). From a pedagogical point of view, it is difficult for instructors to create a discussion task that motivates learners as most textbook problems focus on numbers, operations, or producing a correct answer. Another reason is the difficulty in using external representational tools, such as symbols, diagrams, charts, and graphs, in online text-based discussion environments.

Instructors' Use of Online Discussion Strategies

This section is organized into three parts: 1) discussion design, 2) discussion facilitation and monitoring, and 3) discussion assessment.

Discussion Design

Discussion grouping. An instructor can design an online discussion forum as a whole-class discussion or as a small group discussion. While the whole-class discussion has an advantage of providing students an opportunity to interact with all students in a class, some studies found that students were more active or preferred discussions with a small group (Hew et al., 2010; Lee & Martin, 2017; Schellens & Valcke, 2006). For instance, one study (Jahng, Nielsen, & Chan, 2010) compared students' communication patterns in small group and whole-group activities. The results indicated that some inactive students in a whole-group discussion setting appeared to be more active in a small group setting. Moallem (2003) noted that the small group discussion makes students feel a greater need to participate in the discussion. Also, it makes it easier for instructors to monitor students' contribution as well as team progress. The studies

reported that an appropriate size for a discussion group was approximately ten students per group (Hew et al., 2010; Schellens & Valcke, 2006).

Type of question prompts (or discussion tasks). In asynchronous online discussions, question prompts play a significant role in facilitating students' interactions and higher-order thinking (Choi, Land, & Turgeon, 2008; Ertmer et al., 2011). Thus, it is important for instructors to create effective question prompts or discussion tasks that are suitable for their learning objectives and contexts (Wang, 2014).

Several studies have explored how different types of questions prompts are associated with student interactions or learning outcomes. For instance, Darabi et al. (2013) conducted a meta-analysis study to investigate effective discussion tasks that led to better learning outcomes. The discussion tasks were coded either as application tasks (e.g., asking students to apply a learned rule to a situation) or as elaboration tasks (e.g., justification or substantiation of the topic). The results indicated that application tasks had a much larger effect on performance than elaboration tasks.

Other studies found that each type of question prompts was associated with different outcome variables, such as the quantity of interactions or higher-order thinking, although the findings were contradictory. Specifically, Ertmer et al. (2011) examined how question prompt types influenced the quantity of students' interactions and higher-order thinking in ten different online learning courses. The results showed that opened-ended question types, for example, brainstorming questions (i.e., students are asked to freely interpret or discover the material), were associated with the quantity of interactions (e.g., the number of posts and replies), while lower-level divergent questions were effective in facilitating higher-order thinking. Similarly, Poscente and Fahy (2003) also

found that open-ended questions (or horizontal questions), which did not have correct answers to the problem, were positively associated with subsequent student interactions. However, in contrast to these findings, the result of Bradley, Thom, Hayes, and Hay (2008)'s study indicated that brainstorming questions were influential in promoting higher-order thinking, while limited-focal questions influenced the quantity of interaction (e.g., word count).

Facilitation and Monitoring

Instructor participation. The studies of the instructor's participation in online discussions tended to show mixed results.

Some studies found that instructor participation played an important role in online discussions (Lee & Martin, 2017; Xie, Debacker, & Ferguson, 2006). For instance, one study (Lee & Martin, 2017) showed that students preferred having the instructor facilitate the online discussions to having a peer as a discussion facilitator. Student reports indicated that they wanted the instructor to provide answers to discussion task-related or content-related questions.

In contrast, a number of studies showed that instructor participation has little or even negative effects on students' learning. Findings of a meta-analysis study (Bernard et al., 2009) indicated that teacher-student interaction had lower effects on achievement outcomes than student-student and student-content interactions. In addition, one study (Mazzolini & Maddison, 2007) found that instructor participation (the number of instructors' posts) negatively influenced the quantity of student interactions, for example, the number of students' posts and the average length of their messages.

Other studies showed that the effects of instructor participation varied depending

on the types of instructor participation. For instance, Hoey (2017) found that overall instructor participation (the frequency of the instructor's posts) had no significant effect on student performance. However, when instructor participation was classified into seven types (instructional, encouraging, questioning, conversational, acknowledging, evaluative, operational), the results indicated that instructional posts improved students' perceptions of their learning, and conversational posts were positively associated with students' perceptions of the instructor, course quality, and academic achievement.

Similarly, another study (Belcher, Hall, Kelley, & Pressey, 2015) also found that certain types of instructor participation, such as instructor messages directly related to the student's subject, complimenting the student's post, summarizing the student's post, had significant positive correlations with student performance, although the correlation strengths were low.

Feedback. It is widely agreed that providing timely and meaningful feedback to students is essential to improve the quality of online learning (DeNoyelles, Zydney, & Chen, 2014; Hattie & Timperley, 2007; Woods & Bliss, 2016)**.** Feedback provided by instructors can be divided into three types: elaborated feedback (e.g., providing an explanation), feedback on the correctness of the answer, and feedback providing the correct answer only (Van Der Kleij, Feskens, & Eggen, 2015). Among these three types of feedback, findings of a meta-analysis study indicated that elaborated feedback had the largest positive effect sizes on learning outcomes, followed by providing the correct answer, and feedback regarding the correctness of the answer (Van Der Kleij et al., 2015). The results also revealed that the effect sizes of elaborated feedback were larger for mathematics learning, compared to other subjects, such as social sciences, science,

and languages. Note that this framework was used in this study.

However, although elaborated feedback was more effective than other types of feedback, one study (Nandi, Hamilton, & Harland, 2012) found that an instructor tended to provide simple feedback more often than elaborated feedback. Specifically, the study explored the types of feedback provided by the instructor in an online discussion in a programming course. The result indicated that 50% of messages posted by the instructor were direct answers to questions, while none of the messages were related to facilitating the discussion.

Assessment

It has been argued that the assessment of students' discussion messages is important for facilitating students' interactions and improving the quality of online learning (Andresen, 2009; Lee, 2014; Woods & Bliss, 2016).

Pettijohn et al. (2007) compared the effects of two different conditions, discussion as a required activity and as a voluntary activity, on students' achievement in psychology courses. The result indicated that the students performed significantly better when student participation was mandatory and graded, compared to when participation was optional. Another study (Gilbert & Dabbagh, 2005) also found that assessing students' discussion posts promoted students' deep understanding of course content as well as enhance the overall quality of online discussion.

Hura (2010) examined students' perspective on how discussion posts should be graded. Before the students started their online discussions, most of the students (70%) answered that discussions should be graded for their quality of content or contribution, while few students (18%) answered that the discussions should be graded for

participation only. However, after the students completed the discussion activities, many students changed their perspectives on grading discussions: a majority of the students (62.5%) answered that discussions should be graded for participation only. The students noted that they wanted to freely discuss what they learned and share ideas, rather than to be restricted by a grading or evaluation rubric.

Table 1 summarizes the findings of prior studies reviewed in the study.

Table 1

Findings of the Studies of Instructors' Use of Online Discussion Strategies

Discussion strategies		Findings
Discussion design	Discussion grouping	Students are more active in or prefer discussions with a small group (Hew & Cheung, 2010; Jahng, Nielsen, & Chan, 2010; Lee & Martin, 2017; Schellens & Valcke, 2006)
	Type of question prompts (or discussion tasks)	Mixed findings across the studies. In general, open-ended question types were associated with an increased quantity of interactions (Ertmer et al., 2011; Poscente & Fahy, 2003)
Facilitation and Monitoring	Instructor participation	Mixed findings across the studies. The effects of instructor participation varied depending on the types of instructor participation (Belcher et al., 2015; Hoey, 2017)
	Feedback	Elaborated feedback is more effective than other types of feedback (Van Der Kleij et al., 2015).
Assessment	Use of grades	Students performed significantly better when student participation was mandatory and graded (Gilbert & Dabbagh, 2005; Pettijohn, Terry, & Pettijohn, 2007)

Learner Interactions in Online Discussions

The review of the literature found extensive studies on how students engage in online discussions and can be roughly categorized into two areas:

- Quantitative aspects of learner interactions in online discussions (i.e., participatory behaviors): how participation behaviors (e.g., number of posts, number of views) are associated with outcome variables (e.g., Bainbridge et al., 2015; Dennen, 2008; Hung, Rice, & Saba, 2012; Macfadyen & Dawson, 2012; Warnock, Bingham, Driscoll, Fromal, & Rouse, 2012; Waters, 2012; Yukselturk & Top, 2013)

- Qualitative aspects of learner interactions in online discussions

    1) How the content of online discussions relates to students' learning outcomes (e.g., Çelik, 2013; Hou, 2011; Jahng et al., 2010; Nandi et al., 2012; Wang, 2008; Xie & Ke, 2011; Yeh, 2010),

    2) Exploring interaction patterns between learners or messages (for example, social network analysis, sequential pattern analysis) (e.g., Calvani, Fini, Molino, & Ranieri, 2010; Hou, Chang, & Sung, 2008; Jahng et al., 2010).

The previous literature related to asynchronous online discussions tended to focus on the quantity of interactions, such as the number of messages posted by each student, the words in a message, rather than on the qualitative aspects of interactions (Yang, Richardson, French, & Lehman, 2011). However, purely quantitative data is not sufficient to assess the quality of students' learning processes or group knowledge constructions (Lucas, Gunawardena, & Moreira, 2014). Thus, in this study, both the quantity (students' participatory behaviors) and the quality of learner interactions in online discussions, in particular, discussion content, are examined.

Quantitative Aspects of Learner Interactions in Online Discussions

(Participatory behaviors)

Most studies of students' participatory behaviors have relied primarily on students' posting activities, whereas students' non-posting activities, such as checking for new messages, reading other students' posts, or reflecting on others' comments, have been neglected in the literature (Xie, 2013). However, some studies found that students spent considerable time on non-posting (or lurking) behaviors, often more time than posting activities (Dennen, 2008; Wise, Marbouti, Hsiao, & Hausknecht, 2012).

For this reason, some researchers argued that students' non-posting activities deserve more research attention. Dennen (2008) noted since turn-taking and listening activities are significant in face-to-face dialogue, these non-posting activities should also be examined as an important part of online discussions. Similarly, Wise and colleagues (Wise, Speer, Marbouti, & Hsiao, 2013; Wise, Zhao, & Hausknecht, 2014) cautioned against creating a false dichotomy between students as "producers" vs. "consumers" of content in online discussions. They proposed a framework for examining engagement in online discussions by not just focusing on how students speak online but also on the more covert act of how they listen online. They also argued that these online listening and online speaking behaviors should be measured in terms of not just quantity, but also regarding breadth (i.e., how evenly student behaviors are distributed throughout the discussion) and intensity (i.e., how often student engages and re-engages multiple times (e.g., by re-reading) in a specific thread). This framework was used in this dissertation study.

Nonetheless, relatively fewer studies have empirically explored both students'

posting and non-posting behaviors in online discussions and how these are related to student learning (Dennen, 2008; Wise et al., 2012). For instance, Dennen (2008) asked students to rate on a survey of how their participation behaviors related to learning in blended education courses. Results showed learning by “reading classmates’ messages” received the highest scores, followed by “by reading teachers’ messages,” “by writing messages,” and “by reviewing threads after the discussion ended.”

Recently, with the emergence of learning analytics research, there have been attempts to examine the relationship between students’ discussion behaviors and other variables using students’ clickstream data collected by online learning environments (Bainbridge et al., 2015; Macfadyen & Dawson, 2012; Xie, 2013). For instance, Macfadyen and Dawson (2012) looked at associations between students’ discussion behaviors and students’ final grades in 388 online courses. The result of the correlation analysis revealed the “number of discussion messages read” had the highest significant correlation with students’ final grades, followed by the “number of discussion replies posted,” and the “number of discussion messages posted.” However, these studies simply used the frequency of discussion posts or views and did not consider the breadth or intensity of students’ discussion behaviors. Another study (Bainbridge et al., 2015) explored how students’ online behaviors, including the “number of discussion posts” and “number of discussion messages read” influenced students’ at academic risk status (grade B- or below). The results showed that increases in both variables significantly predicted a decrease in “at academic risk” status, while the number of discussion posts had larger predictor importance than the number of discussion messages read.

In sum, although the vast majority of the work in the area has focused on

students' posting activities, a few empirical studies showed that students' online listening behaviors (non-posting activities), as well as online speaking behaviors (posting activities), are important factors contributing to students' learning.

Qualitative Aspects of Learner Interactions in Online Discussions (Discussion content)

Discussion messages are products of students' learning and collaboration, and content analyses can help reveal underlying information not exposed on the surface of the transcripts (De Wever et al., 2006). Thus, analyzing students' discussion contents can help understand students' learning processes and further provide information for improving instructions and learning environments (Lucas et al., 2014).

In CSCL research, the most widely cited analytical frameworks are: 1) Henri (1992)'s cognitive framework, 2) the Interaction Analysis Model (Gunawardena, Lowe, & Anderson, 1997), and 3) the cognitive presence model (Garrison, Anderson, & Archer, 2001). Henri (1992)'s framework has been cited 2,039 times, the Interaction Analysis Model has been cited 1,955 times, and the cognitive presence model has been cited 367 times as of June 2019, according to Google scholar. The dimensions of the three frameworks are summarized in Table 2. While Henri's model focuses more on students' cognitive aspects, the Interaction Analysis Model focuses on examining the process of the social construction of knowledge and collaborative learning (De Wever et al., 2006).

Although these frameworks have been widely cited in CSCL research, there have been some critiques. First, the frameworks tended to focus on higher-level thinking skills, although most of the students tend to not often exhibit higher-level thinking skills in their discussion messages (Maurino, 2007; Yang et al., 2011).

Table 2

The Analytical Frameworks of Content Analysis Used in CSCL Research

Framework	Theoretical background	Dimensions
Cognitive framework (Henri, 1992)	Cognitive and metacognitive knowledge	- Participative - Social - Interactive - Cognitive: surface processing, in-depth processing - Metacognitive: evaluation, planning, regulation, self-awareness
Interaction Analysis Model	Social constructivism	Phase 1. Sharing and comparing information Phase 2. The discovery and exploration of dissonance among ideas, concepts or statements Phase 3. Negotiation of meaning/co-construction of knowledge Phase 4. Testing and modification of proposed synthesis or co-construction Phase 5. Agreement statements/application of newly constructed meaning
Critical thinking and cognitive presence model (Garrison et al., 2001)	Community of Inquiry	1. Triggering events 2. Exploration 3. Integration 4. Resolution
Yang et al. (2011)	Cognitive and metacognitive knowledge	-Knowledge: Factual knowledge, Conceptual knowledge, Procedural knowledge -Cognitive skills
Online Interaction Model (Ke & Xie, 2009)	Social constructivism	- Social interaction (S) - Knowledge construction (K) • K1: Sharing information • K2: Egocentric elaboration • K3: Allocentric elaboration • K4: Application - Regulation of learning • Reflection • Coordination • Technical issues

For instance, one review found that most of the students' messages were ranked in Phase 1, sharing and comparing information, and few messages went beyond this phase in the studies using the Interaction Analysis Model (Lucas et al., 2014). Second, most of the frameworks used in CSCL research tends to focus on students' cognitive skills, rather

than social interactions (Fu, van Aalst, & Chan, 2016; Ke & Xie, 2009). Lastly, the boundaries between phases in the frameworks are unclear. Some researchers argued that more explicit boundaries and definitions of each phase are necessary (Ke & Xie, 2009; Lucas et al., 2014).

To address these shortcomings of the frameworks, some recent studies developed new frameworks to analyze students' discussion contents. For instance, Yang et al. (2011) developed a content analysis model to assess students' cognitive learning that involves low levels of cognitive skills. Another study (Ke & Xie, 2009) developed the Online Interaction Model that encompasses both learners' cognitive aspects and social interactions by integrating Henri's and Gunawardena et al.'s analytical frameworks (See Table 2). The framework developed by Ke and Xie (2009) was used in this study.

In mathematics learning contexts, a limited number of studies examined what types of discussion messages related to positive learning outcomes (See Table 3).

Table 3

The Analytical Frameworks of Content Analysis Used in Mathematics Learning Contexts

Study	Dimensions
Offenholley (2007)	Soliciting post, Response, Explanation, Evaluation, No math content
Thomas et al. (2008)	-Messages contained genuine mathematical content -Messages focused on group responsibilities -All other messages
Chen et al. (2012)	Knowledge content - correct & new idea, wrong & new idea, the new idea with unknown validity, repetition, justification, no mathematics content Social metacognition - agreement, disagreement, incorrect evaluation, correct evaluation, question, command
Vogel et al., (2016)	-Constructive activities -Dialectic transactivity -Dialogic transactivity

The studies revealed that students' messages that were both interactive (responding to other peers) and evaluative were positively associated with learning outcomes. For instance, Vogel et al. (2016) investigated how different types of collaborative learning activities were associated with freshman students' argumentation skills. The students' discussion messages were categorized into one of the three categories, constructive activities (i.e., self-construction without taking the other peers' contributions), dialogic transactivity (i.e., taking the other peers' contributions without critiques or integrations), and dialectic transactivity (i.e., taking the other peers' contributions in an argumentative way, with critiques or integration). The results indicated that messages related to dialectic transactivity were positively associated with students' argumentation skills.

Another study (Chen et al., 2012) examined what types of students' discussion messages increased the likelihood of the creation of correct, new ideas in the following messages. The results showed that messages coded to "justifications" (e.g., using data or warrant to support a new idea), "correct evaluations" (e.g., agree with the previous message or disagree with the wrong idea), and "asking questions" categories increased the likelihood of students' creation of correct, new ideas in the following messages.

However, as shown in Table 3, the studies conducted in mathematics learning contexts also tended to focus on only cognitive aspects of students' learning, excluding other dimensions such as social interactions. In addition, these studies did not use frameworks used in other CSCL research, which makes it difficult to link or compare the results with other CSCL studies.

Summary of the Literature Review

First, with regard to the use of asynchronous discussion in mathematics learning contexts, some studies demonstrated that the use of online discussions positively influenced students' learning in mathematics learning contexts, although there is still a lack of empirical evidence. In addition, pedagogical and technical challenges remain to be addressed.

In terms of the use of instructors' discussion strategies, the prior studies have shown that purposefully structured online discussions or a domain-specific discussion task promoted learner interactions in online discussions and learning outcomes. However, the studies yielded mixed results depending on the learning contexts. Thus, further studies are needed to better understand the effective discussion strategies that enhance meaningful learner interactions in online discussions and achievement outcomes in mathematics learning contexts.

Lastly, in terms of the quantity of students' interactions, the studies showed that both online speaking and listening behaviors significantly predicted learning outcomes (Bainbridge et al., 2015; Macfadyen & Dawson, 2012). Regarding the quality of learner interactions in online discussions, the studies revealed that students' interactive and evaluative activities were positively associated with learning outcomes in mathematics learning contexts.

However, the vast majority of the work has focused on students' posting behaviors (online speaking behaviors), whereas scant attention has been paid to non-posting behaviors (online listening behaviors). In addition, the studies analyzed the

quality of learner interactions in online discussions in mathematics learning contexts tended to focus only on cognitive aspects and ignored other dimensions, such as social interactions.

CHAPTER III

METHODOLOGY

Methodological Approach: Learning Analytics

The study used a *data-driven* approach by applying “learning analytics” techniques. Learning analytics refers to “the measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs” (Siemens & Baker, 2012, p.252). Based upon the definition of learning analytics, this study aimed to understand instructors’ effective use of discussion strategies and learners’ interactions in online mathematics courses through measurement, analysis, and reporting of instructor and learner discussion data collected by a Learning Management System.

To rigorously examine the effect of an instructional strategy, experimental designs that use random assignment of subjects to different groups are commonly used in educational research. However, designing and conducting random assignment experiments with tight controls often raises the issue of generalizability and the ecological validity to a wide variety of instructional contexts; they also have potential social costs (Koedinger, Mclaughlin, Bier, & Jia, 2016). In learning analytics research, a study uses large amounts of real-time data collected from a wide variety of naturally occurring learning contexts. Thus, it has an advantage of increasing generalizability of the study result with a lower cost.

Learning analytics research typically takes a posthoc analysis approach, which is

different from traditional experimental research (Wise & Shaffer, 2015). A traditional experimental study uses models of learners or instructors derived from learning theories, and then apply the model to practice (Theories of learning → Model design → Instruction design → Practice). On the contrary, a learning analytics study uses data collected from educational practices and then attempts to find meaningful patterns or information within the data to redesign instructions or to contribute to theories of learning (Practice → Data → Discovery → Theories of learning).

In recent years, an increased interest in learning analytics has emerged due to the rapid growth of online education. One of my previous studies (Lee & Recker, 2018) reviewed 47 studies that used learning analytics methods. The results of the systematic review showed that most studies focused on learner behaviors, while remarkably few studies looked at the instructor or course-related data, which is similar to a trend in CSCL research (Maurion, 2007). In addition, the vast majority of the work has used quantitative data capturing learner interactions in online discussions, such as simple counts of user activities, whereas few studies have sought to examine textual or content data.

The Knowledge Discovery in Databases (KDD) Process

The study followed the Knowledge Discovery in Databases (KDD) process, which is a widely used process framework in data mining, learning analytics, and educational data mining research (Baker & Yacef, 2009; Romero & Ventura, 2007). KDD refers to “the nontrivial process of identifying valid, novel, potentially useful, and

ultimately understandable patterns in data" (Fayyad, Piatetsky-Shapiro, & Smyth, 1996, p. 30).

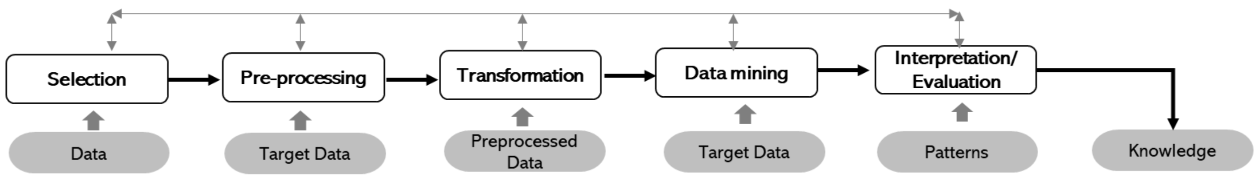

Figure 2. The Knowledge Discovery in Databases (KDD) process[1]

KDD consists of five phases: 1) selection, 2) pre-processing, 3) transformation, 4) data mining, and 5) interpretation/evaluation (See Figure 2).

In the selection phase, researchers learn about an application domain, set a goal for the application, and select a target dataset, such as data samples or a subset of variables depending on the goal of the application. The pre-processing phase includes data cleaning, such as removing noise, irrelevant items, or outliers, and handling missing data. The transformation phase refers to transforming data into an appropriate shape for applying data mining algorithms, for instance, transforming numerical values into ranges, or creating a summary table for further analyses. The data mining phase includes choosing appropriate data analysis techniques (e.g., classification, prediction, clustering), data mining algorithms, and performing data analysis. Lastly, in the interpretation/evaluation phase, researchers interpret the discovered patterns and also incorporate findings into the learning systems or existing theory/knowledge.

[1] Adopted from Fayyad, Piatetsky-Shapiro, & Smyth (1996)

Automatic Analysis of Online Discussion Data

To measure students’ discussion behaviors, this study applied automated analyses of online discussions, which is one form of learning analytics research (Ludvigsen, Cress, Law, Stahl, & Rosé, 2017). There are several advantages of using automatic content analysis (Mu, Stegmann, Mayfield, Rosé, & Fischer, 2012). First, it helps reduce the time required for analyzing the huge body of online discussions by hand as well as training human coders, thus accelerating the progress of research. Also, it enables researchers to analyze discussions messages along multiple dimensions at the same time. Further, it can inform the design of adaptive collaborative learning support, such as individualized feedback or scaffolds, to enhance the quality of learners’ knowledge constructions during online discussions.

There are two general strategies for performing automated analysis of online discussion messages: 1) a fully automated method (using an unsupervised machine learning approach) such as Linguistic Inquiry and Word Count (LIWC) (Kovanovic et al., 2016) and 2) a semi-automated method (a semi-supervised learning approach), which requires hand-coding a subset of the dataset in order to train a machine learning model (Wang, Yang, Wen, Koedinger, & Rosé, 2015; Wen, Yang, & Rosé, 2014). The model is then used to classify the remainder of the dataset. Mu et al. (2012) argued that semi-automated analysis is preferred because manual segmentation by a human can result in more sophisticated and context-specific analyses.

Methods and Procedures

Research Context and Sample

This study used data automatically collected by a Learning Management System (LMS), Canvas, used at a public university located in the Western U.S. The Canvas system recorded a log of all of students' and instructors' interactions, with dates and timestamps, as well as student/instructor textual data, such as discussion prompts, messages, and replies. These Canvas data were made available to an academic-support (AS) unit at the university, which then anonymized the data to protect user privacy. The AS unit then made the data available as multiple files for further analysis.

The sample for the study included instructors and students in fully-online introductory (0 and 1000 levels) mathematics/statistics courses offered between 2011 fall and 2015 summer semesters. The number of courses during the period was 137 courses, and the unique number of instructors who taught these courses is 16. The unique number of students enrolled in these courses was 3,381 students, and 26.0% of the students (n = 880) were enrolled in two or more courses. The average class size was 40 (SD = 25.4).

Next, irrelevant records to the focus of the study were eliminated. Among the 137 courses, 20 courses lacked final course grade data, and 45 courses did not use discussion features, such that these 65 courses were eliminated. The number of courses included in data analyses was 72, a 47.4% reduction from the original 137 courses in the raw datasets. The unique number of instructors who taught 72 courses was 11, and six out of 11 instructors taught the courses more than once. The unique number of students enrolled in these courses was 2,404, and 15.7% of these students (n = 378) were enrolled in more

than one course. Finally, Table 4 summarizes the number of courses, instructors, students, and TAs before and after performing data cleaning.

Table 4

The Number of Courses, Instructors, Students, and TAs Before and After Data Cleaning

		Instructors		Students		TAs	
	# of Courses	# of instructors	unique # of instructors	# of students	unique # of students	# of TAs	unique # of TAs
Online math courses	137	188	16	4,577	3,381	88	30
Courses with final grades & discussion use	72	98	11	2,869	2,404	83	28
Percent of decrease	-47.4%	-47.9%	-31.3%	-37.3%	-28.9%	-5.7%	-6.7%

The instructors in 72 courses posted 711 discussion topics, and the total number of feedback messages posted by the instructors was 1,157 messages. The total number of discussion messages posted by the students was 20,884 messages. The Teaching Assistants (TAs) in these courses also posted 50 discussion messages. However, these (TAs data) were excluded in the further analysis as 1) they posted a relatively small amount of feedback messages compared to instructors, and 2) feedback provided by TAs was not the focus of the study. Finally, Figure 3 summarizes sample sizes included in the study, consisting of four levels of hierarchy (course, students, activities, events/actions).

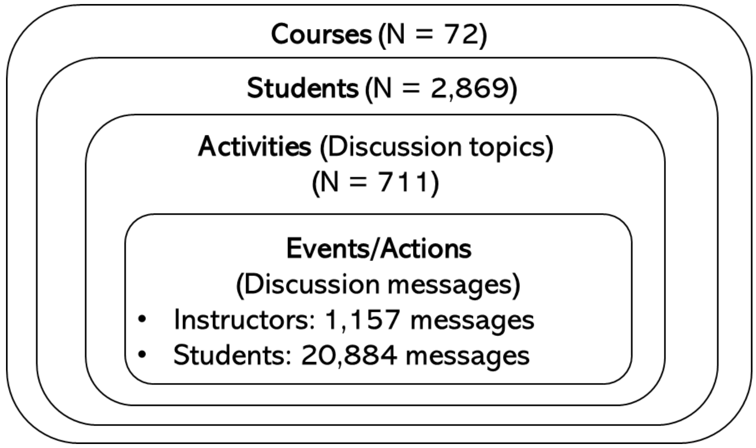

Figure 3. Summary of sample sizes after data cleaning with the different levels of hierarchy

Research Design and Procedures

This study used a quantitative and non-experimental research design. The study was guided by the KDD process, and Figure 4 summarizes the research procedures.

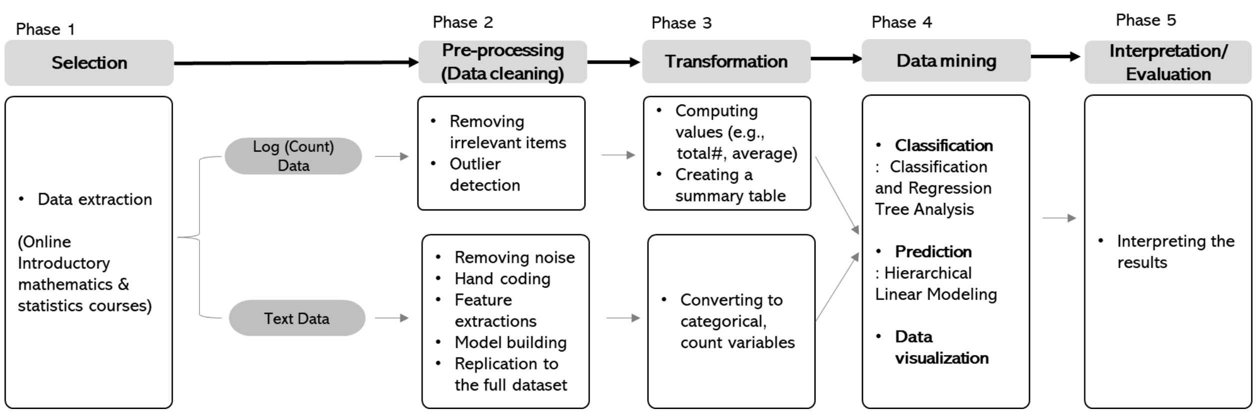

Figure 4. Research procedures guided by the KDD process

Phase 1: Selection

The course, instructor, and student data in online introductory mathematics and statistics courses offered between 2011 fall and 2015 summer semesters were extracted

from an MS-SQL database. The Canvas data consisted of two primary data types, log data (e.g., number of views, timestamps) and content data, such as discussion and chat messages. For the study, the log data was extracted from 18 different tables (e.g., “course_sections,” “enrollments,” “discussion_entries”), and the content data was extracted from four different tables (e.g., “discussion_entries_content,” “discussion_topics_content”).

Phase 2: Pre-processing

Irrelevant items, such as columns or rows that were not related to the study were removed in the log data. For instance, the students who did not have course final grades were eliminated for further analysis. For the textual data, noise (e.g., HTML tag such as <p>, <strong>) in the discussion messages was cleaned. Then, semi-automated content analysis was conducted to extract the constructs needed for data analysis. The details of content analysis procedures are explained in the pre-processing: content analysis section.

Phase 3: Transformation

The data was transformed into appropriate shapes for further analysis. Each value was converted into a new data type (e.g., a string to numeric) to suit the research questions, and summary tables were created for each data analysis.

Phase 4: Data Mining

The data analyses were conducted using the summary tables created in the transformation phase. The technical methods used in learning analytics or educational data mining research are categorized into five types: prediction, clustering/classification, relationship mining, distillation for human judgment (e.g., visual data analytics), and discovery with models (Bienkowski, Feng, & Means, 2012). In this study, two technical

methods were used, specifically prediction and classification. These methods are described in the data analysis section.

Phase 5: Interpretation / Evaluation

Finally, the results of the data analysis were interpreted and compared with the previous findings in the review of the literature.

Measurement

Instructors' use of discussion strategies (course-level variables)

For Research Question 1 (course-level analysis) and Research Question 2 (course-level analysis), instructors' use of online discussion design strategies was measured in terms of three constructs identified from the review of previous literature: *discussion design*, *discussion monitoring and facilitation,* and *discussion assessment*. Operational definitions and examples of each construct are summarized in Appendix A.

First, discussion design consisted of three sub-constructs: discussion grouping, types of discussion settings, and types of discussion tasks. Regarding discussion grouping, each course was classified into one of two categories, a course that used "whole-class discussions" and a course that used "small-group discussions."

The types of discussion settings were divided into two categories, "focused discussions," which allowed participants to post one level of reply to an initial posting, and "threaded discussions," which allowed participants to respond directly to each other, enabling infinite threading of replies. The courses that used both types were labeled as

"mixed discussions."

The types of discussion tasks were categorized into two types: "open-ended discussions" and "closed-ended discussions" (Ke & Xie, 2009). The discussion tasks that did not fall into these two types (e.g., discussions for other purposes, such as "introduce yourself") were labeled as "others."

Second, discussion facilitation and monitoring were measured in terms of two sub-constructs: instructor participation (the quantitative aspect) and types of feedback (the qualitative aspect). In this study, instructor participation was defined as instructors' posting a message on the discussion thread. The feedback types provided by instructors were first divided into three types based on the previous literature: elaborated feedback (e.g., providing explanations), feedback regarding the correctness of the answer, and providing the correct answer (Van Der Kleij et al., 2015). However, a preliminary analysis of feedback messages posted by instructors revealed that some of those were non-instructional, not directly related to course content. For this reason, a few more categories were added to the categorization, such as questioning, encouraging, acknowledging, conversational, and operational feedback messages (Hoey, 2017).

Lastly, discussion assessment was measured with one sub-construct, use of grades, which indicated whether or not an instructor graded discussion messages posted by students. The courses that the instructors graded a part of students' discussion messages were labeled as "partially graded."

Learner interactions in online discussions (student-level variables)

For Research Questions 2 (course-level analysis) and Research Question 3

(student-level analysis), learner interactions in online discussions were measured in terms of quantitative aspects (participatory behaviors), and qualitative aspects. To measure students' participatory behaviors, the analytical framework developed by Wise et al. (2013) was adopted as it encompassed both posting (online speaking) and non-posting (online listening) behaviors. In this study, both behaviors were measured in terms of the quantity (volume of discussion) and the breath (how evenly student behaviors are distributed throughout the discussion).

To measure qualitative aspects of learner interactions in online discussions, the researcher adopted the online interaction model developed by Ke and Xie (2009). This analytical framework was selected because 1) the framework covered both cognitive aspects and social aspects of learner interactions in online discussions, 2) it provided details of definitions and examples of each category and 3) a high inter-rater reliability of the instrument was reported in previous studies, κ =.87 (Ke & Xie, 2009) and κ =.0.92 (Xie & Ke, 2011).

Lastly, to measure students' performance, which was the outcome variable for research question 1 and research question 3 of the study, students' final grades were used. The letter grades were converted into numerical scores on a 4.0 scale.

Finally, Table 5 summarizes constructs, sub-constructs, categories, and how each variable is measured. As previously mentioned, the operational definitions and examples of each construct are provided in Appendix A (instructors' use of discussion strategies) and Appendix B (learner interactions in online discussions).

Table 5

Summary of the Constructs and Variables Used in the Study[2]

Constructs		Categories	Measures	Types of variables	Data sources
Instructors' use of discussion strategies (Course-level analysis)					
Discussion design	Grouping	Whole class	A course that used whole group discussions	Categorical	Log data
		Small group	A course that used small group discussions		
	Types of discussion settings	Focused	A course with focused discussions	Categorical	Log data
		Threaded	A course with threaded discussions		
		Mixed	A course that used both focused and threaded discussions		
	Types of discussion tasks (Ke & Xie, 2009)	Open-ended	$\frac{\#\ of\ open\ ended\ discussions}{Total\ \#\ of\ discussion\ tasks}$	Continuous	Textual data
		Closed-ended & others	$\frac{\#\ of\ closed\ ended\ discussions}{Total\ \#\ of\ discussion\ tasks}$	Continuous	
Monitoring and Facilitation	Monitoring	Instructor participation	Total # of discussion views by an instructor	Continuous	Log data
			Total # of discussion posts by an instructor	Continuous	
	Types of Feedback (Hoey, 2017; Van Der Kleij et al., 2015)	Elaborated feedback	$\frac{\#\ of\ elaborated\ feedback}{Total\ \#\ of\ feedback\ messages}$	Continuous	Textual data
		Providing the correct answer or correctness of the answer	$\frac{\#\ of\ KCR/KR\ feedback}{Total\ \#\ of\ feedback\ messages}$	Continuous	
		Encouraging	$\frac{\#\ of\ encouraging\ feedback}{Total\ \#\ of\ feedback\ messages}$	Continuous	
		Conversational	$\frac{\#\ of\ convertational\ feedback}{Total\ \#\ of\ feedback\ messages}$	Continuous	
		Operational	$\frac{\#\ of\ operational\ feedback}{Total\ \#\ of\ feedback\ messages}$	Continuous	
Assessment	Use of grades	Graded	A course which graded students' posts	Categorical	Log data
		Not graded	A course which did not grade students' posts		
		Partially graded	A course which partially graded students' posts		
Learner interactions in online discussions (Student-level analysis)					
Participatory behaviors (Wise et al., 2013; 2014)	Online speaking	Quantity	Total # of new messages made by a student	Continuous	Log data
			Average message length (in words)	Continuous	

[2] Note that the operational definitions of each variables are in the Appendix.

Constructs		Categories	Measures	Types of variables	Data sources
		Breadth	$\frac{\#\ of\ threads\ with\ a\ minimum\ of\ one\ message}{total\ \#\ of\ threads\ in\ a\ course}$	Continuous	
	Online listening	Quantity	Total # of replies made by a student	Continuous	
			Total # of views of (any) discussion threads by a student	Continuous	
		Breadth	$\frac{\#\ of\ threads\ read\ at\ least\ once}{total\ \#\ of\ discussion\ threads\ in\ a\ course}$	Continuous	
Qualitative aspects of Interactions (Ke & Xie, 2009)	Social interactions (S)		Percentage of the messages related to social interactions (e.g., greetings, appreciation)	Continuous	Textual data
	Reflection (R)		Percentage of messages related to self-evaluation or self-regulation on learning process	Continuous	
	Coordination (C)		Percentage of messages related to teamwork planning or collaboration	Continuous	
	Operational (O)		Percentage of messages related to technical issues, syllabus, assignments clarification	Continuous	
	Knowledge constructions				
		Sharing Information (K1)	Percentage of messages regarding sharing information	Continuous	
		Egocentric elaboration (K2)	Percentage of messages elaborating one's own arguments	Continuous	
		Allocentric elaboration/ (K3)	Percentage of messages comparing or synthesizing peers' multiple perspectives	Continuous	
		Application (K4)	Percentage of messages related to the application of new knowledge	Continuous	
Outcome variables					
Course Performance	RQ1: Average of students' final grades in each course (out of 4.00)			Continuous	Log data
Learner interactions in online discussions	RQ2: Measures of descriptive statistics of learner interactions in online discussions			Continuous	
Student Performance	RQ3: Students' final grades (out of 4.00)			Continuous	

As indicated in Table 5, most of the variables used in the study were measured using the log data directly extracted from the LMS (e.g., the total number of discussion views by an instructor) or computed values using the log data (e.g., percentage of threads with a minimum of one message posted). Some variables, such as "types of discussion

tasks," "types of feedback," were measured using textual data. The details of the content analysis process are discussed in the following section.

Pre-processing: Content Analysis

Before performing data analyses to address the research questions, content analysis was conducted to measure three constructs, "types of discussion tasks," "types of feedback," and "quality of learner interactions in online discussions." Among the three constructs, the "types of discussion tasks" were fully hand-coded because 1) the amount of the data (n = 711) was relatively small, and 2) many of the discussion prompts overlapped with each other as the instructors directly copied the discussion prompts from their previous courses. The other two constructs, "types of feedback" and "quality of learner interactions in online discussions" were semi-automatically coded using a text-mining tool. The frequencies of each category (the results of descriptive statistics analyses) are reported in the results section.

Semi-automated Content Analysis

A semi-automated content analysis was conducted using a text-mining tool, LightSIDE, which was developed by researchers at Carnegie Mellon University for natural language processing (NLP) (Mayfield, Adamson, & Rosé, 2013). Based on the training data hand-coded by a human (on a small subset of data), the tool develops a classification model using machine learning algorithms. Then, additional data is automatically coded based on the developed classification model. The content analysis

was conducted following the procedures described next.

Hand-coding (producing a training dataset)

First, a small subset of data was hand-coded to create a training dataset. As the amount of hand-coded data directly influences the performance of a classification model, previous studies were consulted to help determine the amount. The most commonly used metrics for evaluating a performance of a classification model are *accuracy*, which indicates how many cases a model labeled correctly (Farrow, Moore, & Gašević, 2019), and *Kappa* coefficients, which refers to how well a model performed above chance (Mayfield et al., 2013). Although there is no rule of thumb cut-off points in these metrics, an accuracy of ≥ 70% and Kappa coefficients of ≥ .60 were reported as satisfactory in automated content analysis (Farrow, Moore, & Gašević, 2019).

One study (Wen et al., 2014) conducted by the developers of LightSIDE hand-coded approximately eight to ten percent of the whole discussion messages, and accuracies of the models ranged from 61.0% to 72.3% (Kappa coefficients were not reported). Another study (Wang et al., 2015) hand-coded half of the discussion messages and accuracies ranged from 74.3% to 82.1%, and Kappa coefficients ranged from 0.24 to 0.53. Based on these results, the researcher decided to hand-code 9% to 10% of the messages first and to increase the amount of training dataset if the evaluation metrics (accuracy, Kappa) are not satisfactory.

Regarding a unit of analysis, there are divergent opinions across researchers (Lucas et al., 2014; Strijbos, Martens, Prins, & Jochems, 2006). This study used a “message” as a unit of analysis, following other research using LightSIDE (Wang et al., 2015; Wen et al., 2014).

The discussion messages selected for hand-coding were selected from a stratified random sample along three dimensions: 1) message length, 2) the level (depth) of the messages (in threaded discussions), and 3) the amount of overall interactions of each course. Thus, 10 percent of instructors' feedback messages (n = 120) and 9 percent of students' discussion messages (n = 1,780) were sampled for hand-coding.

To code discussion messages, the study used a general inductive approach (Thomas, 2006), which aims to identify the core themes or categories in each message. Coding was conducted independently by two researchers following the definitions and examples of the measures provided in Appendix A and Appendix B.

A graduate student who studies learning sciences was hired as a second coder. First, the researchers had a meeting to check the clarity of the initially defined categories. After reaching an agreement on the coding schemes, each researcher coded a small subset (1 – 3%) of the total messages independently. Then, the researchers had a meeting again to check the coding consistency and to discuss the clarity of the categories. After reaching an agreement on the revised coding schemes (definitions and examples), the rest of the subset dataset was coded by two researchers independently.

Finally, the Inter-Rater Reliabilities (IRR; Cohen's kappa coefficient) were calculated; the result of the IRR analysis for "types of instructors' feedback" was $\kappa = .908$, and the result of the IRR analysis for "quality of learner interactions in online discussions" was $\kappa = .711$, which indicated that there was a good level of agreement between the two coders (Rosé et al., 2008).

The hand-coded datasets were imported to LightSIDE to build classification models. However, the results showed that evaluation metrics were not satisfactory in the

first attempt in that accuracies ranged from 47.5% to 65.0%, and κ ranged from 0.16 to 0.33. For this reason, another 40% of the messages (approximately half of the messages in total) were hand-coded to create training datasets, following procedures used by a previous study that used LightSIDE (Wang et al., 2015). Additional messages were hand-coded by the researcher because the two coders already had reached a good level of agreement.

The number of hand-coded discussion messages for creating training datasets are summarized in Table 6.

Table 6

The Number of Discussion Messages Handed-coded for Creating Training Datasets

Constructs	Total # of messages	# of messages handed-coded (1st attempt)	Total # of messages hand-coded
Types of instructors' feedback	1,157	120 (10%)	562 (49%)
Quality of learner interactions in online discussions	20,884	1,780 (9%)	10,400 (50%)

Extracting features

The handed-coded datasets were imported into LightSIDE to extract features. The tool provides fourteen different options for feature extractions, such as unigram (i.e., marks the presence of a single word within a message), bigrams (i.e., marks the presence of two consecutive words), trigrams (i.e., marks the presence of three consecutive words), or the Part of Speech (POS) bigrams (i.e., captures a sentence structure within a message, for example, "personal pronoun + a non-third person singular present verb"), line length

(i.e., marks the number of words in a message), contain non-stop words (i.e., contain content words; useful when analyzing instant message conversations), and so forth (Mayfield et al., 2013).

These feature extraction options can be selected at the same time, and each combination of the options produces different results depending on the nature of the training dataset (Rosé et al., 2008). One study (Rosé et al., 2008) recommended to use “unigrams” plus “punctuation” features after comparing eight different feature combinations. However, Kovanovic et al. (2016) noted that the use of these features is dataset dependent because the classification space is defined by data itself. For this reason, eight different feature combinations compared in Rosé et al. (2008)’s work were considered in the study because 1) there existed too many feature combinations to consider all possible combinations, and 2) to compare the results to previous work.

Building a model

After setting up the feature extraction options, classification models were built based on machine learning algorithms. LightSIDE provides several built-in algorithms: Naïve Bayes classifier (default), logistic regression, and Support Vector Machines (SVM). Each algorithm has pros and cons: Naïve Bayes and logistic regression are good at classifying messages with multiple possible categories, while the SVM algorithm is optimized for binary choices (e.g., Yes/No). These three algorithms were considered in further analyses of automated content analysis using LightSIDE.

Testing the validity of the model / Model comparison

LightSIDE provides several built-in functions for testing the validity of the model and to help with model selection. To test the validity of the trained model, it provides N-

fold cross-validation. The N-fold cross-validation splits the training dataset into folds and holds out one of the folds at each turn to measure accuracy. For instance, in 10-fold cross-validation, the training dataset is split into ten subsets. At the first turn, it treats nine subsets as training sets and one of the subsets as a test set and then measures the accuracy of the model. The final accuracy (as a percent) is measured by repeating these turns nine times.

Finally, Table 7 and Table 8 show the results of evaluation metrics for eight different feature spaces and three different machine learning algorithms for instructors' feedback messages, and students; discussion messages, respectively. Note that bold values are the highest.

Table 7

The Comparison of Evaluation Metrics for Different Feature Spaces and Different Machine Learning Algorithms (for Instructors' Feedback Messages)

	Naïve Bayes classifier		Logistic regression		SVM	
	accuracy	κ	accuracy	κ	accuracy	κ
Unigrams	63.9%	0.46	**76.2%**	**0.61**	71.9%	0.56
Unigrams & line length	64.1%	0.46	75.4%	0.60	71.9%	0.56
Unigrams & POS bigrams	64.1%	0.46	75.4%	0.60	71.9%	0.56
Unigrams & bigrams	63.5%	0.45	75.6%	0.60	72.2%	0.56
Unigrams & punctuation	63.9%	0.46	75.8%	0.61	72.4%	0.56
Unigrams & stemming	64.2%	0.47	75.8%	0.61	72.1%	0.56
Unigrams & contain non-stop words	63.9%	0.46	75.6%	0.60	72.2%	0.56
Unigrams, line length, punctuation, & contain non-stop words	63.9%	0.46	74.9%	0.59	72.2%	0.56

Table 8

The Comparison of Evaluation Metrics for Different Feature Spaces and Different Machine Learning Algorithms (for Students' Discussion Messages)

	Naïve Bayes classifier		Logistic regression		SVM	
	accuracy	κ	accuracy	κ	accuracy	κ
Unigrams	61.2%	0.50	73.5%	0.64	69.8%	0.60
Unigrams & line length	60.7%	0.49	74.4%	0.66	69.8%	0.60
Unigrams & POS bigrams	58.8%	0.48	73.0%	0.64	68.8%	0.58
Unigrams & bigrams	61.4%	0.50	74.0%	0.65	70.4%	0.60
Unigrams & punctuation	61.5%	0.51	73.7%	0.65	70.3%	0.60
Unigrams & stemming	61.0%	0.50	73.9%	0.65	70.1%	0.60
Unigrams & contain non-stop words	61.2%	0.50	73.5%	0.64	69.8%	0.60
Unigrams, line length, punctuation, & contain non-stop words	61.2%	0.50	**74.7%**	**0.66**	70.4%	0.60

The accuracies and Kappa coefficients of each classification model were compared. For instructors' feedback messages, as shown in Table 7, the model with "unigrams" feature and "logistic regression" algorithms had the highest accuracy (76.2%) and Kappa coefficient (κ = 0.61) among the 24 classification models and showed satisfactory evaluation metrics (accuracy ≥ 70%, κ ≥ .60). For students' discussion messages, the model with "unigrams, line length, punctuation and contain non-stop words" features and "logistic regression" algorithms showed the highest accuracy (74.7%) and Kappa coefficient (κ = 0.66), which was similar to Rosé et al. (2008)'s results.

The tool also automatically produces a confusion matrix, which shows the incidence of actual labels against predicted labels (false positive and negatives). It also allows for creating multiple confusion matrixes produced by several trained models,

which makes it easier for a researcher to choose the best model. The confusion matrices for the final models are provided in Table 9 and Table 10. In addition, after checking the confusion matrices, “allocentric elaboration (K3)” and “application (K4)” in students’ discussion messages were merged into one category as only six messages were labeled as K4 category.

Table 9

Confusion Matrix for Instructors’ Feedback Messages

Predicted / Actual	Conversational (CON)	Elaborated Feedback (EF)	Encouragement (ENC)	KCR/KR feedback	Operational (OPE)
CON	20	11	4	2	16
EF	3	253	1	2	26
ENC	8	3	14	0	4
KCR/KR	2	12	0	8	3
OPE	4	30	1	2	133

Table 10

Confusion Matrix for the Quality of Learner Interactions in Online Discussions

Predicted / Actual	Coordination (C)	K1	K2	K3	K4	Reflection (R)	Social Interaction (S)	Operational (O)
C	4	3	0	0	0	1	7	4
K1	1	2046	129	73	0	103	390	74
K2	0	288	594	152	0	30	31	17
K3	0	122	133	676	0	5	8	11
K4	0	0	3	2	0	0	1	0
R	0	108	25	2	0	495	163	25
S	1	227	22	5	0	117	3499	50
O	0	127	15	10	0	40	111	450

Application of the trained model to the rest of the dataset

For instructors' feedback messages, the model with "unigrams" feature and "logistic regression" algorithms was chosen for the application of the trained model. To measure the quality of students' interactions (students' discussion messages), the model with "unigrams, line length, punctuation and contain non-stop words" features with "logistic regression" algorithms were selected for application of the trained model. Finally, these developed models were applied to the rest of the datasets for fully automated content analysis.

Data Analysis

Classification and Regression Tree (CART) Analysis

For research question 1, a decision tree analysis was performed to examine what online discussion strategies were associated with positive student performance. The advantages of decision tree analysis are that it: 1) is a non-parametric method that does not assume normal distribution of data, 2) is robust to outliers, missing values, heavily skewed data, 3) provides feature or variable importance information, and 4) produces an interpretable visual output (Kazemitabar, Amini, Bloniarz, Berkeley, & Talwalkar, 2017; Lemon, Roy, Clark, Friedmann, & Rakowski, 2003; Mendez, Buskirk, Lohr, & Haag, 2008; Song & Lu, 2015).

There are several different decision tree algorithms, such as Classification and Regression Tree (CART), C4.5, Chi-squared Automatic Interaction Detection (CHAID), and Quick, Unbiased, Efficient, Statistical Tree (QUEST). Among the algorithms, the

CART algorithm was selected because 1) both categorical and continuous variables can be used as dependent variables, and 2) it is more robust to outliers than C4.5 (Song & Lu, 2015).

CART analysis progressively segments samples into subgroups by identifying which variables (and in what order) best predict the outcome variable. The process repeats until no further splits are possible and terminal nodes are created, which are "mutually exclusive and exhaustive subgroups" of the entire sample (Lemon et al., 2003, p.173). In order to choose the optimal size of the terminal nodes, 7-fold cross-validation was performed as the sample size (N = 72) was close to a multiple of seven. In 7-fold cross-validation, the training dataset was split into seven subsets. At the first turn, six subsets were selected as a training set, and one of the subsets was chosen as a test set and then measured the accuracy of the model. The final accuracy was computed by repeating these turns six times.

To explore to what extent different structures designed into online discussions have impacts on learner interactions in online discussions (research question 2), a CART analysis was used to classify into subgroups. The measures of descriptive statistics of learner interactions in online discussions for each subgroup (e.g., mean, median, standard deviation) were used to compare the level of learner interactions in online discussions. Also, the Kruskal-Wallis H test was performed to examine whether there were significant statistical differences in the level of learner interactions in online discussions between the subgroups.

Hierarchical Linear Modeling (HLM)

To investigate what types of learner interactions in online discussions were associated with positive student performance (research question 3), Hierarchical Linear Modeling (HLM) (also referred to as multilevel modeling) was performed as students (N = 2,869) were nested within 72 courses.

The advantages of HLM are that it: 1) can accommodate non-independent of observations, 2) can handle a lack of sphericity, and 3) is robust to missing data (Woltman, Feldstain, MacKay, Rocchi, 2012).

Although the eleven predictors of learner interactions in online discussions had different scales (see Table 5), mean centering was not conducted because all variables (e.g., number of messages made by a student, average message length) had meaningful values of zero (i.e., non-arbitrary zero points) (Peugh, 2010).

Four separate models were created to explore the relationships between learner interactions in online discussions and students' final grades.

Model 1 was a nonconditional (also referred to as variance components) model with no predictors to compute Intraclass Correlation Coefficient (ICC), in other words, how much of the variance in the students' final grades was attributable to students and courses.

Model 1 (Level-1) $Y_{ij} = \beta_{0j} + \varepsilon_{ij}$

(Level-2) $\beta_{0j} = \gamma_{00} + \mu_{0j}$

In the Level-1 equation, Y_{ij} indicates the student final grade for a student *i* in

course j. β_{0j} refers to the mean final grades of the students in a course j, and ε_{ij} is a student-specific random error term. In Level-2 equation, γ_{00} indicates students' overall mean final grade, and μ_{0j} means a course-level random error term.

Next, the eleven predictors of learner interactions in online discussions (the participatory behaviors and the quality of learner interactions in online discussions) were included in a model to explain the variation in the students' final grades. To explore how a model changed when including the quality of learner interactions in online discussions to students' participatory behaviors, two separate models were created. In model 2, the predictors reflecting students' participatory behaviors (the quantity and the breadth of learner interactions in online discussions) were included as the Level-1 predictors. In model 3, the predictors reflecting the quality of learner interactions in online discussions were added to model 2. The equations are formulated as below, and ε_{ij} indicates the variance unexplained after controlling for the student-level predictors.

Model 2 (Level-1): $Y_{ij} = \beta_{0j} + \beta_{1j}$(online speaking-quantity) + β_{2j}(online speaking-breadth) + β_{3j}(online listening-quantity) + β_{4j}(online listening- breadth) + ε_{ij}

Model 3 (Level-1): $Y_{ij} = \beta_{0j} + \beta_{1j}$(online speaking-quantity) + β_{2j}(online speaking-breadth) + β_{3j}(online listening-quantity) + β_{4j}(online listening- breadth) + β_{5j}(quality-K1) + β_{6j}(quality-K2) + β_{7j}(quality-K3/K4) + β_{8j}(social interactions) + β_{9j}(reflection) + β_{10j}(operational) + β_{11j}(coordination) + ε_{ij}

Finally, the course-level predictors were included in the Level-2 model to investigate the relationship between instructors' use of discussion strategies (course-level variables) and course mean final grades. Among the ten variables of instructors' use of discussion strategies, the variables selected in the CART analysis (important variables in predicting the students' final grades) were included in the model (See Table 15 in Chapter 4). Thus, the fully specified model (Model 4) is as follow. In the equation, μ_{0j} indicates the variance unexplained after controlling for Level-2 predictor variables.

Model 4 (Level-2): $\beta_{0j} = \gamma_{00} + \gamma_{01}$(open-ended prompts) + γ_{02}(elaborated feedback) + γ_{03}(grading) + γ_{04}(focused setting) + μ_{0j}

Finally, Table 11 summarizes the input variables, outcome variables, analysis methods, and tools used in the study.

Table 11

Summary of Variables, Analysis Methods, and Tools Used in the Study

	Input variables	Outcome variables	Analysis methods	Tools
Data pre-processing			-Data cleaning -Content analysis (Text mining)	SQL server management studio LightSIDE
RQ1. What online discussion strategies are associated with positive student performance?	Instructors' use of discussion strategies	Average of students' final grades in each course (out of 4.00)	Decision Tree: Classification and Regression Tree (CART)	R studio
RQ2. To what extent do different structures designed into online discussions impact the kinds of learner interactions in online discussions?	Instructors' use of discussion strategies	Different Level of learners' interactions in online discussions	-Kruskal-Wallis H Test -Descriptive statistics	R studio
RQ3. What types of learner interactions in online discussions are associated with positive student performance?	Level of learners' interactions	Students' final grades (out of 4.00)	Hierarchical Linear Modeling (HLM)	R studio

CHAPTER IV

RESULTS

Descriptive Statistical Analysis

Before performing data analyses to address the research questions, descriptive statistical analyses were performed to better understand the data. The frequencies were calculated for categorical variables (See Table 12), and means, standard deviations, minimum and maximum values were computed for continuous variables (See Table 13 and Table 14).

Table 12

Frequencies for Instructors' Use of Discussion Strategies (N = 72 courses)

Variable	Number of courses	Percent
Grouping		
Whole class	69	95.8%
Small group	3	4.2%
Discussion settings		
Focused	19	26.4%
Threaded	31	43.1%
Mixed (both focused and threaded)	18	25.0%
Not specified (N/A)	4	5.6%
Use of grades		
Graded all discussion messages	7	9.7%
Not graded	47	65.3%
Partially graded	18	25.0%

Table 13

Descriptive Statistics for Instructors' Use of Discussion Strategies

(N = 72 courses)

	Mean	*SD*	*Min.*	*Max.*
Types of discussion tasks				
Open-ended	0.64	0.26	0.00	1.00
Closed-ended & Others	0.37	0.26	0.00	1.00
Monitoring				
Instructor view	74.31	89.61	0	424
Instructor participation	16.46	24.86	0	111
Types of feedback				
Elaborated feedback (EF)	0.37	0.32	0.00	1.00
Providing answers (KCR/KR)	0.02	0.05	0.00	0.33
Encouraging feedback	0.04	0.14	0.00	1.00
Conversational feedback	0.09	0.21	0.00	1.00
Operational feedback	0.48	0.35	0.00	1.00

Table 14

Descriptive Statistics for Learner Interactions in Online Discussions

(N = 2,869 students)

	Mean	*SD*	*Min.*	*Max.*
Participatory behaviors				
# of new messages made	7.13	11.92	0.00	129.00
average message length (words)	329.95	250.95	0.00	3164.00
% of threads posted at least once	0.49	0.30	0.00	1.00
# of replies made	2.64	6.93	0.00	102.00
# of views of any discussion threads	31.36	53.31	0.00	947.00
% of threads read at least once	0.53	0.45	0.00	1.00
Quality of learner interactions in online interactions				
Sharing information (K1)	0.12	0.20	0.00	1.00
Egocentric elaboration (K2)	0.05	0.12	0.00	1.00
Allocentric elaboration/Application (K3/K4)	0.04	0.10	0.00	0.82
Reflection (R)	0.02	0.08	0.00	0.77
Social interactions (S)	0.73	0.34	0.00	1.00
Operational (O)	0.04	0.11	0.00	1.00
Coordination (C)	0.00	0.03	0.00	1.00
Performance				
Students' final grades (out of 4.00)	2.00	1.55	0.00	4.00

Next, two Pearson correlation analyses were performed to explore the associations between 1) instructors' use of discussion strategies and students' final grades, and 2) learner interactions in online discussions and students' final grades. Note that categorical variables (e.g., grouping, use of grades) were not included in the Pearson correlation analyses.

The correlation heatmap represented in Figure 5 shows the correlation coefficients between instructors' use of discussion strategies and students' final grades. In the heatmap, color gradients range from darker red for $r = -1.0$ to darker blue for $r = 1.0$.

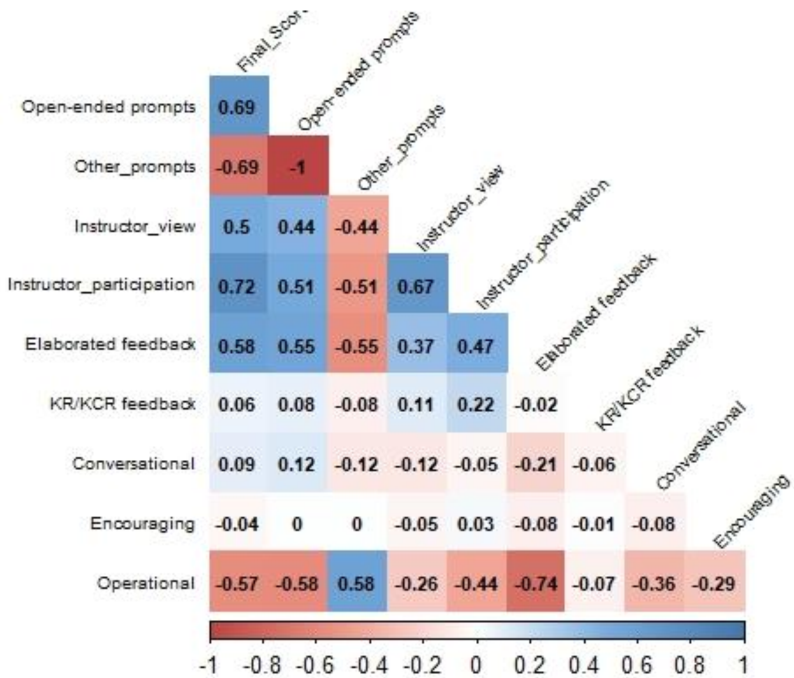

Figure 5. Pearson correlations between instructors' use of discussion strategies and students' final grades

As shown in the first column of the heatmap in Figure 5, among the eight continuous variables of instructors' use of discussion strategies, "instructor participation (the frequency of discussion posts)" showed the strongest positive correlation with

students' final grades (r = .72, p < .05). The ratio of "open-ended prompts" (r = .69, p < .05) and the ratio of "elaborated feedback" (r = .58, p < .05) also showed the significant and positive correlations with students' final grades. However, the ratio of "closed-ended/other prompts" (r = -.69, p < .05) and the ratio of "operational feedback" (r = -.57, p < .05) had the significant and negative correlations with students' final grades.

Figure 6 demonstrates the correlation coefficients between learner interactions variables and students' final grades.

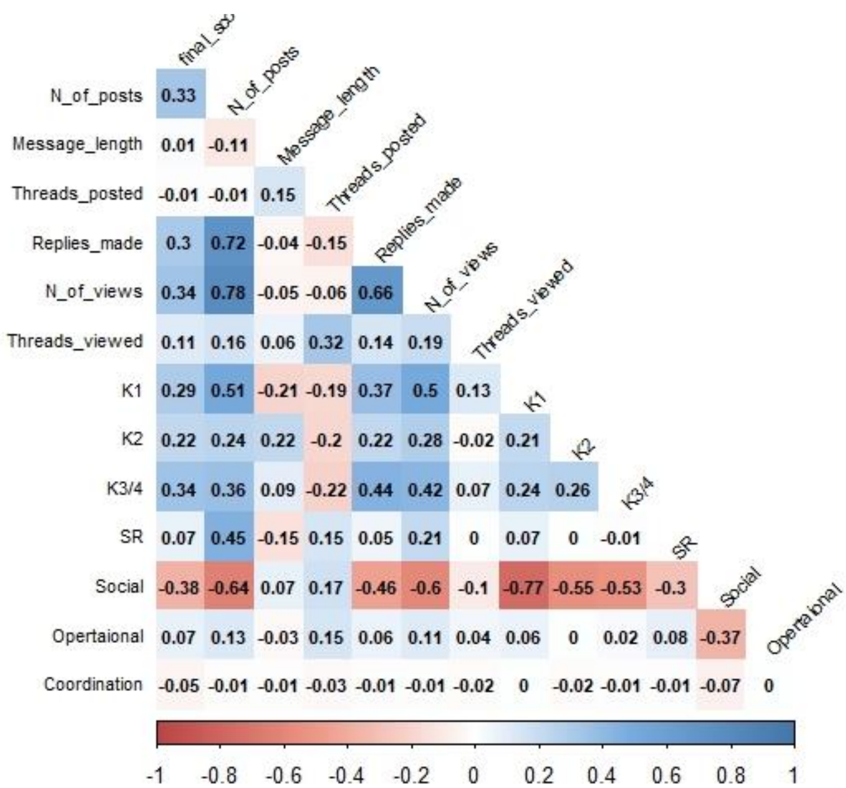

Figure 6. Pearson correlations between learner interactions in online discussions and students' final grades

Among the six variables measuring learner participatory behaviors, "the number of views (the quantity of online listening behaviors)" had the strongest positive

association with students' final grades *(r* = .34, *p* < .05). In terms of the quality of learner interactions in online discussions, "the ratio of K3/K4 messages (messages related to allocentric elaboration/application)" showed the strongest positive correlation with students' final grades (*r* = .34, *p* < .05). However, "the ratio of social interaction messages" (*r* = - .38, *p* < .05) showed a significant and the highest negative correlation with students' final grades.

Research Question 1: Instructors' Use of Discussion Strategies and Course Performance

A CART analysis was conducted to investigate the effect of instructors' use of discussion strategies on students' final grades. As mentioned earlier, 7-fold cross-validation was performed to choose the optimal size of the terminal nodes. As shown in Figure 7, the minimum cross-validation estimate of error (also called x-error; Y-axis in Figure 7) occurred at five terminal nodes with x-error = 0.258, suggesting the optimal size of the terminal nodes was five. The prediction error rate in cross-validation (root node error * the minimum x-error * 100%) was estimated as 0.414 * 0.258 * 100% = 10.7%.

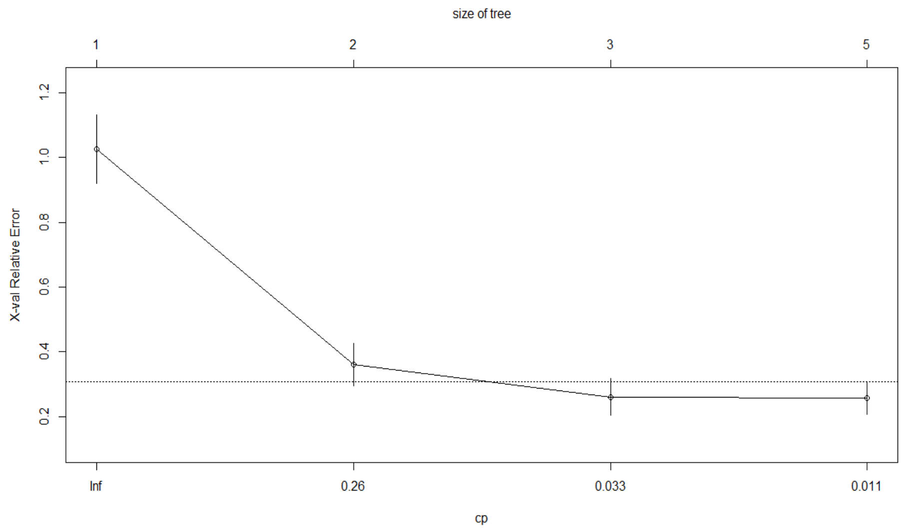

Figure 7. Cross-validation relative error (x-error) for the classification and regression tree

Figure 8 depicts the classification and regression tree, predicting students' final grades. Among the 12 variables included in the classification and regression model (See Table 5 in Chapter 3), only four variables were included in the tree construction.

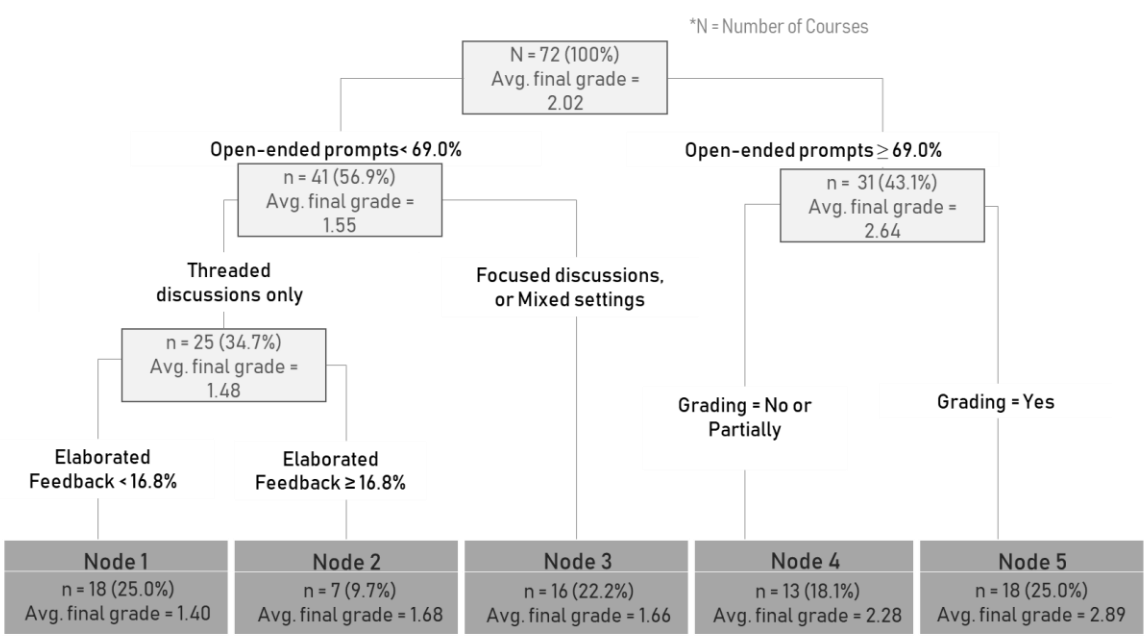

Figure 8. Classification and regression tree predicting final course grades

The CART revealed that the most important variable associated with higher course final grades was “ratio of open-ended prompts,” explaining 69.93% of the total variance in final grades. The next variables selected for splitting were “grading (9.45%)”, followed by “discussion settings (1.03%), and “ratio of elaborated feedback (1.00%)”. Eight other variables of instructors’ use of discussion strategies; grouping, using threaded discussion settings, the percentage of closed-ended or other prompts, instructor participation (the number of view and posts), feedback related to providing the correct answer (or correctness of the answer), the percentage of encouraging feedback, and the percentage of conversational feedback, were not included in the model in predicting students’ final grades.

Table 15

The Summary of Classification Rules Predicting Final Course Grades [3]

Terminal node	Rule	Final grades	# of courses in the node
1	If “% of open-ended prompts” < 0.69 (69%) “used threaded discussions only” “ratio of elaborated feedback” < 0.08 (8%)	1.40	17
2	If “% of open-ended prompts” < 0.69 (69%) “used threaded discussions only.” “ratio of elaborated feedback” ≥ 0.08 (8%)	1.64	8
3	If “% of open-ended prompts” < 0.69 (69%) “used focused discussions or mixed settings.”	1.66	16
4	If “% of open-ended prompts” ≥ 0.69 (69%) “no grading or partially graded discussion messages posted by students.”	2.28	13
5	If “% of open-ended prompts” ≥ 0.69 (69%) “graded all discussion messages posted by students”	2.89	18

[3] See Table 5 in Chapter 3 for full descriptions of the variables.

Table 15 summarizes the classification rules predicting final course grades. To summarize, the courses that used more open-ended prompts (≥ 69.0%) and graded all discussion messages posted by students, used focused discussions or mixed discussion settings and provided more elaborated feedback (≥ 8.0%) had higher final course grades than the courses which did not.

Finally, Table 16 shows the means for the instructors' use of discussion strategies in the five terminal nodes identified in the CART analysis. Each terminal node was defined based on the summary statistics: Node 1: *Closed-ended & Non-grading discussion design with Operational feedback*, Node 2: *Threaded-discussion design*, Node 3: *Focused-discussion design*, Node 4: *The Highest number of discussion topics (threads)*, Node 5: *Open-ended discussion design & Grading with Elaborated feedback.*

Table 16

Means of Instructors' Use of Discussion Strategies for Each Terminal Node

	Node1 (n = 17)	Node2 (n = 8)	Node3 (n=16)	Node4 (n=13)	Node5 (n=18)
No. of discussion topics posted	2.92	6.62	2.19	21.77	17.27
# of courses with small group	0	0	0	0	3
# of courses with focused/mixed	0	0	16	6	15
# of courses with grading	0	1	0	6	18
Types of discussion tasks					
Open-ended prompts	41.18%	47.77%	51.74%	66.19%	85.61%
Closed-ended & Others	58.82%	52.23%	48.26%	33.81%	14.39%
Monitoring and facilitation					
Instructor view	27.76	39.81	48.26	72.18	119.22
Instructor participation	3.23	4.33	4.10	9.24	37.81
Types of feedback					
Elaborated feedback	19.48%	25.97%	27.65%	32.64%	53.68%
Providing answers	1.38%	0.25%	0.16%	0.57%	2.48%
Encouraging	4.47%	1.20%	3.91%	1.66%	4.31%
Conversational	6.38%	8.51%	5.93%	9.89%	14.21%
Operational	68.29%	64.07%	62.34%	55.25%	25.32%

Research Question 2: Instructors' Use of Discussion Strategies and Learner Interactions in Online Discussions

For the research question 2, to explore to what extent structures designed into online discussions impacted on the level of learner interactions, the measures of descriptive statistics of learner interactions in online discussions for each node were used. Table 17 summarizes the means of learner interactions in online discussions for each terminal node identified in the CART analysis.

Table 17

Means of Learner Interactions in Online Discussions for Each Terminal Node

	Node1	Node2	Node3	Node 4	Node 5	Kruskal-Wallis H Test χ^2	p
# of students in each node	686	472	594	310	807		
Avg. final grades	1.40	1.64	1.66	2.28	2.89		
Participatory behaviors							
# of new messages	1.00	1.77	1.06	14.15	17.23	1649.70	< .01
average message length	326.46	331.00	329.01	203.87	381.41	169.00	< .01
% of threads posted	54.66%	50.74%	55.81%	51.35%	36.48%	158.06	< .01
# of replies made	0.06	0.19	0.13	1.82	8.42	1453.71	< .01
# of views	6.65	11.72	6.69	33.56	81.18	1197.49	< .01
% of threads read	65.60%	46.40%	43.43%	23.68%	63.96%	250.24	< .01
Quality of learner interactions in online discussions							
Sharing information (K1)	1.58%	3.35%	1.45%	10.56%	32.45%	1580.25	< .01
Egocentric elaboration (K2)	0.32%	1.24%	0.19%	1.01%	14.07%	1307.61	< .01
Allocentric elaboration/Application (K3/K4)	0.09%	0.14%	0.08%	0.40%	11.17%	1139.65	< .01
Reflection (R)	0.16%	0.81%	0.00%	13.13%	1.90%	519.68	< .01
Social interactions (S)	94.54%	90.28%	95.91%	70.10%	35.46%	1629.46	< .01
Operational (O)	3.31%	4.17%	2.02%	4.79%	4.73%	433.39	< .01
Coordination (C)	0.00%	0.00%	0.35%	0.02%	0.22%	15.17	< .01

The students in Node 1 (n = 686, "*Closed-ended & Non-grading discussion design with Operational feedback"*) showed the highest value of percentage of threads read (65.60%: the breadth of online listening behaviors), meaning that the students more evenly accessed the discussion threads than the students in other nodes. However, in terms of the quality of learner interactions in online discussions, most of their discussion posts (94.54%) were labeled "social interactions," which were not directly related to course content.

Similarly, the students in Node 2 (n = 472, "*Threaded-discussion design"*), which had similar discussion designs with the courses in Node 1, also showed a higher percentage of social interactions messages (90.28%).

The students in Node 3 (n = 594, "*Focused-discussion design"*) showed the highest value of percentage of threads posted (55.81%; the breadth of online speaking behaviors), which indicates that the students in this node more evenly contributed to the discussion threads than those in other nodes. However, similar to Node 1 and Node 2, most of the discussion posts (95.91%) were categorized into social interactions.

While the instructors in Node 4 (n = 310, "*The highest number of discussion topics"*) created more discussion topics (threads) than the courses in other nodes, the students in this node showed the lowest value of the breadth of online listening behaviors (23.68%), meaning that the students' accesses were focused on certain discussion threads. The students in this node also showed the highest proportion of the messages related to reflection (13.13%: self-evaluation or self-regulation on their learning process), and the lowest average message length (203.87 words) among the five nodes.

Lastly, the students in Node 5 (n = 807, *Open-ended discussion design & Grading*

with Elaborated feedback) showed the highest values of the quantity of online speaking (e.g., number of new messages made, average message length) and online listening behaviors (number of views, number of replies made). Also, most of their messages (57.69%) were labeled between K1 (sharing information) to K3/K4 (allocentric elaboration/application), indicating that they were directly related to course content.

To explore whether there are statistically significant differences between the levels of learner interactions in online discussions between the five nodes, Kruskal-Wallis H tests were conducted. As shown in Table 17, there were statistically significant differences in all variables of learner interaction in online discussions between the nodes.

Research Question 3: Learner Interactions in Online Discussions and Course Performance

In order to investigate to what extent the variables of learner interaction in online discussions predicted students' final grades (research question 3), a two-level hierarchical linear model analysis was conducted.

Before building prediction models, high correlation coefficients between some variables of learner interactions in online discussions (Level 1 predictors) were detected in the correlation analysis (See Figure 6), implying substantial multicollinearity problems which might lead to inefficient parameter estimates. One study (Shieh & Fouladi, 2003) noted that the standard errors of parameter estimates become too large to claim a statistical significance when the correlation coefficient between two predictors is .75. The result of the Pearson correlation analysis showed that "number of views" had high

correlation with "number of new messages posted (r = .78, p < .05)", and "messages of social interactions (S)" also had strong correlation with "messages of sharing information (K1)" (r = -.77, p < . 05), both with correlation coefficients larger than .75. For this reason, "number of new messages posted" and "messages of social interactions" were excluded from further analyses. Note that between the two variables which had substantial multicollinearity problems (e.g., "number of views" and "number of new messages posted"), the variables which had weaker positive correlations (e.g., number of new messages posted) with the outcome variable (the students' final grades) were removed.

Table 18 shows the results of the four models predicting the students' final grades. First, Model 1 (variance components model) examined whether there was significant variation in the Level 1 residuals and Level 2 means, in other words, whether the students' final grades varied across the courses. The proportion of variation on the students' final grades that lied between the courses was 15.5% ($\rho\ (\mathrm{ICC}) = \frac{\sigma^2{}_{course}}{\sigma^2{}_{course} + \sigma^2{}_{error}} = \frac{0.37}{0.37+2.02} = 0.155$), indicating that there was significant variation across the courses on the students' final grades (ICC > .05) (Huta, 2014). The variance between the students was 84.5%.

Model 2 investigated to what extent the students' participatory behaviors (the quantity/breath of learner interactions in online discussions) predicted the students' final grades. The results showed that four variables were statistically significant predictors of the students' final grades, "percentage of threads read" (β = .53, p < .05), "percentage of threads posted" (β = .41, p < .05), "the number of new messages made" (β = .02, p < .05), and "the number of replies made" (β = .02, p < .05). The "average message length"

was not statistically significant (β = .00, p > .05). Model 2 including the students' participatory behaviors explained 88.5% of the variation in the students' final grades among the students and 11.5% of the variation in the students' final grades among the courses.

Table 18

A Hierarchical Linear Model Predicting Students' Final Grades

	Model 1		Model 2		Model 3		Model 4	
	β	*SE*	β	*SE*	β	*SE*	β	*SE*
Intercept	2.02	0.08	1.43	0.09	1.72	0.10	0.81	0.26
Level 1 (Student-level)								
Participatory behaviors								
# of new messages	-	-	0.02*	0.01	0.01*	0.00	0.01	0.01
avg. message length	-	-	0.00	0.00	0.00*	0.00	0.00*	0.00
% of threads posted	-	-	0.41*	0.12	-0.02	0.14	0.52*	0.20
# of replies made	-	-	0.02*	0.01	0.01	0.01	0.01	0.01
% of threads read	-	-	0.53*	0.11	0.20*	0.09	0.28*	0.10
Quality of learner interactions in online discussions								
Sharing information (K1)	-	-	-	-	0.87*	0.18	0.37	0.22
Egocentric elaboration (K2)	-	-	-	-	1.42*	0.27	0.97*	0.29
Allocentric/Applicat -ion(K3/K4)	-	-	-	-	3.55*	0.33	3.05*	0.36
Self-regulated processes (R)	-	-	-	-	0.14	0.46	0.14	0.52
Operational (O)	-	-	-	-	0.63*	0.26	0.36	0.29
Coordination (C)	-	-	-	-	-2.60*	1.01	-2.58*	1.07
Level 2 (Course-level)								
Open-ended	-	-	-	-	-	-	1.08*	0.35
Elaborated feedback	-	-	-	-	-	-	0.17	0.19
Graded	-	-	-	-	-	-	-0.49	0.26
Focused setting	-	-	-	-	-	-	0.05	0.12
	β	%	β	%	β	%	β	%
Level 1 variance	2.02	84.5%	1.93	88.5%	1.85	97.4%	1.77	97.3%
Level 2 variance	.37	15.5%	.25	11.5%	.05	2.6%	.05	2.7%
Model FIT								
AIC	10,307.05		10164.24		9004.10		6791.11	
BIC	10,324.94		10211.94		9086.10		6891.66	

* p < .05

For Model 3, the variables of quality of learner interactions in online discussions were added to Model 2. The results indicated that five variables of the quality of learner interactions in online discussions and three variables from Model 2 were statistically significant predictors of the students' final grades, "allocentric elaboration/application (K3/K4)" ($\beta = 3.55$, $p < .05$), "egocentric elaboration (K2)" ($\beta = 1.42$, $p < .05$), "sharing information (K1)" ($\beta = .87$, $p < .05$), "operational messages" ($\beta = .63$, $p < .05$), "percentage of threads read" ($\beta = .20$, $p < .05$), "the number of new messages made" ($\beta = .01$, $p < .05$), "average message length" ($\beta = .00$, $p < .05$), and "coordination messages" ($\beta = -2.60$, $p < .05$). Model 3 including both students' participatory behaviors and the quality of learner interactions in online discussions explained 97.4% of the variation in students' final grades among the students and 2.6% of the variation in the students' final grades among the courses.

Lastly, Model 4 fully included the student-level variables and the course-level variables to explore how these variables were related to students' final grades after controlling for the course-level variables, such as the percentage of open-ended prompts, percentage of elaborated feedback, the use of grades, and the use of focused settings. In terms of the course-level variable, only one variable, the "percentage of open-ended prompts" ($\beta = 1.08$, $p < .05$) significantly predicted the students' final grades. Regarding the quality of learner interactions in online discussions, three variables were statistically significant predictors of the students' final grades, "allocentric elaboration/application (K3/K4)" ($\beta = 3.05$, $p < .05$), "egocentric elaboration (K2)" ($\beta = 0.97$, $p < .05$), and "coordination messages" ($\beta = -2.58$, $p < .05$). Three variables of the students' participatory behaviors also significantly predicted the students' final grades, "percentage

of threads posted” (β = .52, $p < .05$), “percentage of threads read” (β = .28, $p < .05$), and “average message length” (β = .00, $p < .05$). Model 4 including the course-level variables explained 97.3% of the variation in students’ final grades among the students and 2.7% of the variation in students’ final grades among the courses.

CHAPTER V

DISCUSSION AND CONCLUSION

Asynchronous online discussion is one of the most widely used instructional methods in online learning environments (De Wever et al., 2006; Hew et al., 2010; Ke & Xie, 2009; Wang, 2008). Previous studies have shown that the use of online discussions helped in improving not only learners' engagement but also higher-ordering thinking and achievement (Bernard et al., 2009; Maurino, 2007; Pettijohn et al., 2007; Salter & Conneely, 2015). Thus, it can be used as one possible solution for improving student success in online mathematics courses. However, while many previous studies have demonstrated the effectiveness of using online discussions, the effective use of online discussions has been seldom studied in mathematics learning contexts.

For this reason, this dissertation study attempted to address the question, "What design strategies for online discussions work best in online introductory mathematics learning courses?" More specifically, the study explored: 1) effective discussion design strategies that enhance meaningful learner interactions in online discussions and student performance and 2) learners' participatory behaviors and interactions patterns that lead to better student performance in online introductory mathematics courses. In particular, the study used a data-driven approach by applying a set of data mining techniques to a large-scale dataset automatically collected by the Canvas LMS for five consecutive years at a public university in the U.S.

Before discussing the results of the study, the results from data preprocessing, in particular, semi-automated content analysis, is discussed because as it is a relatively new

and innovative approach in educational research and also has an important role in this dissertation study.

Findings from a Semi-Automated Content Analysis

To measure the "types of instructors' feedback" (a sub-construct of instructors' use of discussion strategies) and "quality of learner interactions in online discussions" (a sub-construct of learner interactions in online discussions), this study applied a semi-automated content analysis by using a text-mining tool, LightSIDE.

The performance of a classification model (i.e., accuracy and Kappa coefficients) depends on the amount of hand-coded data, feature extractions, and machine learning algorithms. In terms of the amount of hand-coded data, the results showed that it was required to hand-code approximately half of the discussion messages to successfully train the models for classifying the discussion data, with accuracies over 75% and Kappa coefficients over 0.6. This finding was congruent with previous research (Wang et al., 2015; Wen et al., 2014). Specifically, the accuracies ranged from 48% to 65%, and κ ranged from 0.16 to 0.33 when the researcher hand-coded nine to ten percent of the feedback and discussion messages. However, there were approximately 10% to 25% increases in accuracies and 0.27 to 0.44 increases in Kappa coefficients when additional handed-coded data were added to the training datasets.

Regarding feature extractions, eight different combinations of features were compared (See Table 7 and Table 8). The results indicated that using *unigrams* (marking the presence of a single word within a message) for classifying instructors feedback, and

using *unigrams* + *line length* (marking the number of words in a message) + *punctuation* (marking periods, commas, and quotation marks) + *contain non-stop words* (marking the presence of content words) for classifying students' discussion messages showed the best performances among the eight different feature combinations.

Specifically, using solely unigrams feature worked more effectively than combining it with bigrams (marking the presence of two words) or POS bigrams (looking at the structure within the text), which was consistent with findings from the previous work of Rosé et al. (2008). Indeed, Rosé et al. (2008) noted that adding bigrams feature increases feature space size, which made it more difficult for the algorithms to converge on effective models. Similarly, Kovanovic et al. (2016) noted that inflation of feature space size produced too many features even for a small dataset, resulting in the chances of over-fitting the training data.

To automatically classify the students' discussion messages, adding more features such as "line length," "punctuation," "contain non-stop words" (content words) to the unigrams feature showed better performance than using the unigrams feature alone. This result may be due to the fact that the students' discussion messages had a larger variation in their message length compared to instructors' feedback messages. Also, the developer of the tool (Mayfield et al., 2013) noted that the "contain non-stopwords" feature is particularly useful when analyzing message conversations because it distinguishes a message that does not carry any content words within a message (e.g., "Okay").

Summary of Findings

The first research question examined what instructors' use of online discussion strategies were positively associated with students' course performance. Three constructs (discussion design, monitoring, and facilitation, assessment) consisting of twelve variables were included in the CART model. The results of the CART analysis identified five terminal nodes and revealed that the courses that posted more *open-ended prompts*, *graded all discussion messages* posted by students, used *focused or mixed discussion* (both focused and threaded) settings, and provided more *elaborated feedback* had higher students final grades than those which did not. Among the four variables included in the CART model, the ratio of open-ended prompts explained the highest variability in the students' final grades. Eight other discussion strategies, such as grouping, using threaded discussion settings, the percentage of closed-ended or other prompts, instructor participation (the number of view and posts), feedback related to providing the correct answer (or correctness of the answer), encouraging feedback, and conversational feedback were not included in the model in predicting the students' final grades.

The second research question explored the impact of different structures designed into online discussions on the quantity (participatory behaviors) and the quality of learner interactions in online discussions. The Kruskal Wallis H-tests revealed that there were statistically significant differences in all variables of learner interactions in online discussions (13 variables) between the five nodes identified from the CART analysis, implying that the instructors' use of discussion strategies (discussion structures) influenced the quantity (volume of discussions), the breadth (distribution of participation

throughout the discussions) and the quality of learner interactions (levels of knowledge constructions) in online discussions.

Lastly, the third research question investigated to what extent the types of learner interactions in online discussions predicted the students' course performance using a two-level hierarchical linear modeling analysis.

First, the intercept-only model (Model 1) showed an ICC of .155, indicating that 15.5% of the variance in students' final grades was accounted for the courses and 84.5% of the variance in students' final grades was accounted for the students.

When the variables for students' participatory behaviors were included in the model (Model 2), four variables statistically significantly predicted students' final grades: percentage of threads read at least once, number of replies made (both related to the breadth of online listening behaviors), percentage of threads posted at least once (the breadth of online speaking behaviors), and number of new messages posted (the quantity of online speaking behaviors).

However, when the predictor variables measuring the quality of learner interactions in online discussions were added to the model (Model 3), the regression coefficients related to participatory behaviors became much lower. The messages related to allocentric elaboration and application (K3/K4) showed the largest regression coefficients among the predictors, and egocentric discussion messages (K2), messages of sharing information (K1), and operational messages also significantly predicted the students' final grades. The messages related to coordination significantly predicted the students' final grades, but the regression coefficient was negative.

In the final model, (Model 4) including all student-level and course-level

variables, only one variable of instructors' use of discussion strategies, the ratio of open-ended prompts, showed a positive association with the final grades. In terms of learner interactions in online discussions, allocentric elaboration, and application (K3/K4) messages, egocentric (K2) messages, and the *breadth* of online speaking behaviors (percentage of threads read) and online listening behaviors (percentage of threads posted) were positively and significantly associated with students' final grades.

The findings of the study are discussed in the following section. The results for the RQ1 and RQ2 are discussed together because the results for RQ2 are drawn from the CART analysis performed for RQ1.

Discussion of Findings

Instructors' Use of Online Discussion Strategies

Discussion design

Discussion grouping. The discussion grouping variable, in other words, designing a discussion forum as a whole-class discussion or a small group discussion, was not included in the CART model predicting the students' final grades. However, this result may be attributed to the small proportion of the courses that used grouping. Descriptive statistical analyses (See Table 12) showed that only 4% of the courses used small group discussions.

One interesting finding is that the courses that used small group discussions were all contained in Node 5 (Table 16); this node had the highest final grades and the highest average level of learner interactions in online discussions (Table 17) among the five

terminal nodes. This finding supports previous research which found that students were more active in small group discussions because they tended to feel a greater need to participate in the discussions compared to whole-class discussions (Hew et al., 2010; Jahng, Nielsen, & Chan, 2010; Lee & Martin, 2017; Moallem, 2003; Schellens & Valcke, 2006).

Types of discussion settings. In terms of the two discussion settings built into the Canvas LMS, the results of the CART analysis revealed that the courses that used focused discussion settings, which allows one single reply to an initial posting, had higher students' final grades that the courses that used threaded discussion settings only. In particular, all courses in Node 1 with the lowest final grades used threaded discussion settings only, while 83% of the courses in Node 5 with the highest final grades used the focused discussion settings. Also, the students in Node 1 showed the lowest level of learner interactions in online discussions among the five nodes. In terms of the quality of learner interactions in online discussions, only approximately 2% of the discussion messages in Node 1 were directly related to course content (see Table 17).

This finding supports the claim of Gao, Zhang, and Franklin (2013), who argued that threaded forums do not often foster productive online discussions although these are the most commonly used type of discussion settings. They also noted that the use of threaded discussions makes it hard for instructors to promote a focused and in-depth discussion. Thus, it is necessary to design alternative asynchronous discussion environments to improve the quality of online discussions.

Types of question prompts (or discussion tasks). The results of the CART analysis revealed that the percentage of open-ended prompts (> 69%) was the most

important variable in terms of predicting the students' final grades. The percentage of closed-ended prompts or other types of prompts (e.g., introduce yourself) were neither selected for predicting the final grades nor showed a statistically significant and positive association with the final grades (See Figure 5 and Figure 8).

In terms of the association with learner interactions in online discussions, Node 5, which had the highest percentage of open-ended prompts (85.6% of the discussion threads), showed the highest level of the quantity of learner interactions in online discussions. In addition, most of the discussion messages (57.7%) posted by the students in Node 5 were directly related to course content (labeled as K1, K2, K3, and K4). These findings corroborate previous research that the use of open-ended prompts positively influences not only the quantity of interactions (Ertmer et al., 2011; Ke & Xie, 2009; Poscente & Fahy, 2003 Richardson & Ice, 2010) but also the quality of interactions (promoting higher level of knowledge construction) in online discussions (Bradley et al., 2008; Ke & Xie, 2009).

Listed below are examples of open-ended prompts posted by the instructors.

- *Ask and answer questions about Module 11 here. And here's an article for you to read "Your brain is primed to reach false conclusions." It doesn't directly talk about statistics, but it is related to many of the topics we cover in class. Additionally, I think that those of you who are interested in education and psychology will find it especially interesting. It may also help you question your own assumptions and perhaps argue more effectively with your Facebook friends. :)*

- *Ask and answer questions about Module 8 here. If you'd rather read and comment on an article, I suggest "Myth and Reality in Reporting Sample Error." There are also a bunch of others at the bottom of the Module 8 page that are interesting, including a themed (kind of a joke) article called "How many zombies do you know? Using indirect survey methods to measure alien attacks and outbreaks of the undead."*

As shown above, the instructors provided the opportunities for the students to share their thoughts and questions relating to each module. Also, by providing additional reading materials relevant to each topic, it helped the students think more deeply about each topic and connect the math content covered in the courses to the real-word problems (e.g., the reality in reporting sample error). One of the advantages of open-ended discussions is that it provides opportunities for learners to freely contribute their ideas and thoughts without too many restrictions (Richardson & Ice, 2010). This finding has important implications for designing online discussion in introductory mathematics courses. It can be suggested that it is important to provide opportunities for learners to freely discuss course content, rather than creating a discussion task related to producing a correct answer, even in introductory mathematics courses. Ke and Xie (2009) also argued that closed-ended discussions do not provide enough opportunity for learners to share their ideas/thoughts or co-construct meaning with other students. Thus, discussion tasks should be structured around questions that encourage students to develop different perspectives and explanations of a topic in order to promote students' learning.

Facilitation and Monitoring

The CART analysis showed that the ratio of *elaborated feedback*, which provides explanations or additional resources (e.g., hints, additional information, extra study materials) to students, was the only variable included in predicting students' final grades among all the variables included in discussion monitoring and facilitation. Other variables, such as instructor participation (measured by the number of discussion views by an instructor, the number of posts by an instructor), feedback of providing a correct answer or correctness of the answer, encouraging feedback, conversational feedback, and operation feedback, did not significantly predict students' final grades.

In Node 1, 2, and 3 identified from the CART analysis, which had lower final grades than other two nodes, over 60 percent of feedback messages provided by the instructors were "operational feedback", which were related to course information, management (e.g., syllabus, final grades) or students' concerns about technical issues, and not relevant to course content. As a consequence, over 90% of the discussion messages posted by the students in these three nodes (Node 1, 2, 3) were related to social interactions, and thus were off-topic contributions that were not directly related to course content.

These results agree with other studies finding that the effects of instructor feedback on the student' performance or learner interactions in online discussions varied depending on the types of instructor feedback (Belcher, Hall, Kelley, & Pressey, 2015; Hoey, 2017). Like these previous studies, the results in this study also indicated that feedback messages directly related to course content (instructional posts) were positively associated with student performance or the quality of learner interactions in online

discussions. The results also confirmed that it is more important to provide explanations or resources (elaborated feedback) and help students solve the problems by themselves, rather than just providing the correct answer or correctness of the answer to students in mathematics learning contexts (Van Der Kleij et al., 2015).

Assessment

The results showed that the courses that graded students' discussion messages tended to have higher average final grades than the courses which did not. In particular, all courses in Node 4 and Node 5 with higher final grades than other nodes fully or partially graded the students' discussion messages, while none of the courses in Node 1 and Node 3 graded any discussion messages posted by the students.

In terms of the associations with the quantity and the quality of interactions in online discussions, the students showed a higher level of participation and posted more on-topic discussions when their messages were graded. This finding supports previous research which revealed that students performed better (Pettijohn et al., 2007) and showed higher level of knowledge construction (Gilbert & Dabbagh, 2005) when online discussions were mandatory and graded.

Learner Interactions in Online Discussions and Course Performance

The third research question examined how learner interactions in online discussions were associated with the students' final grades. While much of research on asynchronous online discussions have tended to focus on the quantity of learner interactions in online discussions (Yang, Richardson, French, & Lehman, 2011), this research sought to include not only the quantity (volume) of learner interactions, but also

the breadth (distribution of participation throughout the discussion) and the quality of learner interactions in online discussions, as well as non-posting activities, which were defined as online listening behaviors (Wise et al., 2013; 2014).

Regarding learners' participatory behaviors, the results revealed that the breadth, in other words, how evenly the students' contribution are distributed throughout the discussion threads, had a greater impact on the students' final grades than the quantity of student participation, such as how many times the students posted or read a discussion message. In particular, the percentage of threads read at least once, which was the *breadth of online listening behaviors* showed the highest predictive value for the students' final grades among the learner participatory behaviors variables. These findings align with my earlier work (Lee & Recker, 2019), which showed that the breadth of online listening behaviors was the most important variable in terms of predicting students' course performance. These results also are in agreement with the findings of other research (Bainbridge et al., 2015; Macfadyen & Dawson, 2012) that demonstrated that online listening behaviors significantly predicted student course performance. Although extensive research has tended to focus on the learners' online speaking behaviors (e.g., the number of posts, message length) rather than online listening behaviors, these findings support the idea of a number of researchers (Dennen, 2008; Wise et al., 2013; 2014) who argued that online listening behavior is not just non-participating or lurking behaviors, but an important part of online interactions which contribute to students' meaningful learning.

Although the breadth of online speaking and listening behaviors was found to be statistically significant in predicting students' final grades when they were combined with

the variables measuring the "quality" of learner interactions in online discussions, the predictive values of participatory behaviors decreased or became statistically non-significant. This implies that the quality of learner interactions has much greater influences on students' final grades than the quantity or the breadth of learner interactions in online discussions. The higher predictive values of the variables reflecting the quality of learner interactions in online discussions than those of participatory behaviors variables can be explained by the types of discussion content presented in Table 17. More specifically, the students in Node 4 posted 14.15 messages on average during one semester. However, over 70% of their messages were related to "social interactions" (e.g., greeting, emotional expressions, sharing personal life), in other words, off-topic messages not contributing to group knowledge construction. Thus, the findings show that the quantity does not necessarily indicate the quality of learner interaction in online discussions.

Furthermore, the study adopted the online interaction model (Ke & Xie, 2009), which encompasses learners' knowledge construction (K1 – K4), social interaction and self- regulated or self-directed processes, to measure the quality of online interactions. Among the variables, the messages reflecting allocentric elaboration (K3) and application (K4), which were related to *deep and collaborative learning*, showed the highest predictive value for the students' final grades, followed by egocentric elaboration messages (K2), and sharing information (K1).

These results are consistent with those of other studies which found that interactive or evaluative messages (Vogel et al., 2016) and messages related to correcting evaluations (Chen et al., 2012) were positively associated with students' learning

outcomes in online mathematics discussions. In this research, many of the messages labeled as K3 or K4 categories were also related to *comparing or synthesizing peers' multiple solutions* (e.g., "Hi, Alice, my boxes look like Tom below, I used 12 because you have 12 changes to win $2…") or *evaluating or correcting other students' approaches* to solving the problems (e.g., "I think I see where you're going wrong. All the values for your normal cdf are correct except for the last one.."). By evaluating other peers' solutions or comparing their solutions with others through online discussions, learners had opportunities to think about the course content more deeply, which may have led to better course performance.

Limitations and Future Work

Several important limitations need to be considered. First, in terms of the semi-automated content analysis, the study compared eight feature combinations to make it easy to compare the results with previous work. Although the results produced satisfactory evaluation metrics (accuracies and Kappa coefficients), these results may not be the best classification models as there are other feature extraction options (e.g., Trigrams, Stem-N grams) not considered in the study. A future study might explore other feature extraction options to improve the performance of the classification models.

Second, the current study adopted research frameworks developed by other researchers to measure the types of instructors' feedback and the quality of learners' interactions in order to more closely link CSCL research and studies in mathematics learning contexts. For this reason, it was challenging for the researcher when hand-coding

the discussion messages because some of the coding categories were too general. For instance, many different types of elaborated feedback, such as providing hints, additional information, or extra study materials, were identified, but these were all categorized into one category, elaborated feedback. Similarly, for the students' discussion messages, there were different types of allocation (K3) messages, for example, comparing a solution with other peers, or correcting others' solutions. Further research needs to use more specific coding categories to better understand what discussion strategies or learner interaction patterns lead to student success.

The results also revealed questions in need of further investigation. One issue that emerged from the findings is that the students posted few messages related to deep or collaborative learning levels (K3/K4), although these were highly associated with student performance. This finding seems to be consistent with other research which found most messages posted by the students lacked mathematical contents or knowledge (Groth & Burgess; Thomas et al., 2008). Specifically, only 4% of the students' discussion messages were labeled as deep/collaborative learning levels (See Table 14), and 11% of the discussion messages were categorized into K3/K4 levels even for the students in Node 5 with the highest final grades (See Table 17). Similarly, other studies also found that most of the students' messages were labeled as low knowledge construction levels and few messages (e.g., 5% in Ke & Xie's work) were identified at higher knowledge construction levels (Ke & Xie, 2009; Lucas et al., 2014). Future research should, therefore, concentrate on the investigation of discussion strategies that lead to a higher level of knowledge construction.

Lastly, the study only examined the nature of an individual message, and the

relationship between two or more messages was not considered although many of the messages were in threaded formats. Thus, future work should examine the association between messages by applying more advanced data mining techniques, for example, sequential pattern mining.

Contributions and Implications

The main goal of this dissertation study was to explore what discussion structures work best in online introductory mathematics courses. The study has shown that the instructors' use of discussion strategies influenced not only learner interactions in online discussions but also students' course performance. Specifically, using open-ended discussion prompts, evaluating students' discussion messages, using focused-discussion settings, and providing elaborated feedback to students had positive impacts on course performance as well as the quantity, the breadth and the quality of learner interactions in online discussions. Results also showed that the quality of learner interactions in online discussions, in particular, the students' messages related to allocentric elaboration (taking other peers' contributions in argumentive or evaluative ways) and application were positively associated with their course performance.

This work makes several noteworthy contributions to the current literature on learning analytics research, CSCL research, as well as an instructional design practice.

First, in terms of learning analytics research, the study applied semi-automated content analysis, which is a relatively new and innovative approach in educational research. The study informed approach for determining the required amount of hand-

coded data, feature extractions, and machine learning algorithms for effective classification of discussion data. Thus, this research can serve as an example for applying semi-automated content analysis to discussion data, and the methods can be applied to other studies.

Second, regarding CSCL research, the results enhance our understating of instructors' use of discussion strategies and students' non-participation behaviors (online listening behaviors), which has received relatively little attention. Most studies in the field of CSCL have focused on students' behaviors or interactions, in particular, students' posting activities, while the role of instructor involvement and students' posting or non-posting activities have been neglected in the literature. By considering together instructors' use of discussion strategies and the quantity, breadth, and quality of learner interactions in online discussions, the study examined which discussion strategies and learner interaction patterns lead to better learning outcomes. The results of the study also supported the idea that learners showed a higher level of interactions or performed better in effectively designed or structured online discussions (Borokhovski et al., 2012; Darabi et al., 2013; Salter & Conneely, 2015; Vogel et al., 2016).

Lastly, in terms of instructional design practices, the study explored the impact of discussion design and strategies in online mathematics learning contexts, an area seldom investigated. In particular, the findings from this study suggest that it is important to provide opportunities for learners to freely discuss course content, rather than creating a discussion task related to producing a correct answer, even in introductory mathematics courses. Other findings reported in the study can also serve as guidance for instructors or instructional designers on how to design better online mathematics courses.

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APPENDICES

Appendix A

Definitions and Examples of the Measures for Instructors' Use of Discussion Strategies

Types		Definitions	Code	Examples
Instructional feedback		• Posts that are related to students' learning (messages related to course contents or subjects) e.g.,) providing new information to the discussion, clarifying an area of confusion, sharing resources to improve understanding	**INST**	• The box for the number of 3s has one 1 and three zeros. The expected value for the number of threes is 100x.25=25
	Correctness of the answer	• Feedbacks on whether the answer is correct or not. • Does not provide any additional information.	***KR***	• Yes, that's right. Yes, that's exactly it.
	Elaborated feedback	• Providing explanations or additional recourses e.g.,) hints, additional information, extra study materials	***EF***	T-tests are used when the sample size is small and when you are doing a test about the average….
	Correctness of the answer & Elaborated feedback	• Providing feedbacks on 1) whether the answer is correct or not 2) with additional explanations / resources	***KR+EF***	• You are correct. In each version of HANES, they take a different group of people to measure….. Correct. This list of numbers (1, 2, 3, 4, 5) and this list of numbers (3, 3, 3, 3, 3) both have the…
Questioning		• Posts that pose a leading question but offered no information or encouragement • Typically shared to stimulate additional discussion	**QUE**	But which way does the causation go? Is there a third, unseen factor affecting both?
Encouraging		Provide support, affirm a student's position or actions and praise a student for their contribution or actions. (complimenting the student's posts)	**ENC**	• Great answer! • I endorse Melissa's method.
Acknowledging		Messages that recognize a student's contribution to the discussion without offering praise of a specific idea or action.	**ACK**	• That is a great article, thanks for sharing it here! • Great photo….and thanks for sharing.

Types	Definitions	Code	Examples
Coversational	• Messages that are conversational in nature • Not explicitly intended to improve student learning of the content • Use of humor, Expressing emotions, etc.	**CON**	• Module 12. Buy M&M's before listening to the Chapter 28 lectures. :) • Welcome, I'm happy you're in the class. Let me know how I can help you learn the material.
Opertaional	• Messages related to a 1) student's concern about technical issues 2) course information & management (e.g., syllabus, final grades)	**OPE**	• Please also see today's announcement about SoftChalk. Some people are even having trouble accessing the assignment at all right now • No, there are 18 questions for the final.

Appendix B

Definitions and Examples of the Measures for Learner Interactions in Online Discussions

Types		Definitions	Code	Examples
Knowledge construction			**K**	
	Sharing Information	Simply adding facts or opinions **<u>without any elaboration</u>**	***K1***	• The review on cost and acceleration was great • Math is super interesting when you think about it. Numbers doing magical things are interesting.
		Asking a question without any elaboration		• Does the standard deviation always have to contain a decimal point? • Will someone show me how to do number 8 please?
		Simply sharing resources (e.g., website)		
	Egocentric elaboration	Elaborating on the content relevant to given task (e.g., arguments, understanding, problem solutions), but <u>do NOT directly take other students' contribution into account</u>	***K2***	• Interesting read for the article. OK maybe not so interesting coming from a person who does not really like numbers…. • I read the article and I think the polls are laced with many errors especially bias…
		Citing one's own experience/observation or <u>citing books</u>, reading materials and knowledge learned before		• I am thinking it would be a cluster sample. In the book, it didn't mention a volunteer response sample, so I eliminated that option.
	Allocentric elaboration	• Comparing and synthesizing <u>peers' multiple solutions</u> • Integrating: Integrate previous contributions with one's own problem solutions/arguments	***K3***	• Hi Elizabeth, my boxes look like Blairs below...I used the 12 [2] because you have 12 chances to win $2 out of 38 26 [-1] because you have 26 chances to lose the $1..
		Judgment: Evaluating or correcting others' approaches to solve the problems		• I think I see <u>where you're going wrong</u>. All the values for your normal cdf are correct except for the last one, .8… • The question is asking you for the EV sum and not the ave box, you are halfway to your answer! Now that you have the ave box (.4) you need to figure out the EV sum….
		Extended understanding		• Let me take this a step further…

Types		Definitions	Code	Examples
	Application	Application of new knowledge or proposing in-field application strategies (e.g., suggesting a new solution to the problem)	***K4***	• I read the article about some issues in political sampling and how Romney was to win but state polls must be statistically biased.... I found this really interesting because it shows how statistics is used in real life…
Social Interactions:		Off-topic contributions that are NOT clearly related to the task	**S**	
		e.g.) Greetings, Self-introduction, Sharing personal life		• Hi my name is… • Oh okay, thank you, I was really confused. • I'm pretty excited for the new movie!
		e.g.) Appreciation (e.g., thanks)		• Thank you for the help. • Thanks to everyone for all of your help this semester!!!
		e.g.) Agreement without elaboration		• I am with you guys! • Hey, I feel like I am in the same boat. • I am so glad I am not the only one feeling this way!!
		e.g.) Emotional expressions		• I am super nervous for Midterm 2!!
Self- regulated or self-directed processes				
	Coordination	Teamwork planning and coordinating for collaborative projects	***C***	• Maybe we should get a study group together sometime so we can put our brains together to understand things?
	Reflection	Self-evaluation and self-regulation on one's <u>learning process or learning strategies</u>	***R***	
		e.g.) Talking about their own learning progress and strategies (monitoring their own learning)		• I will definetely have to review that topic • I really worked hard studying for this one • This section was the hardest one yet for me… It will just take a lot of time and studying. • Now I feel like I actually understand the concept.
		e.g.) goal setting, planning for future study		• I am going to have to put some serious time in to do well on this quiz.

Types		Definitions	Code	Examples
				• I need lots of practice before the test.
		e.g.) Talking about what they have learned		• This section was fun. I enjoyed the graphs and visually determining the answers. • This section is a nice brake from the past sections
		e.g.) Talking about how they studied this subject		• I have been able to just learn it through the videos and following along with the slides in the workbook. • What I did with my time management for this class is find the dates that are recommended for finishing each exam, then taking the number of lessons for that unit…
	Operational	Questioning and answering on technological problems (e.g., MymathLab, Canvas, computer, web browsers)	***O***	• I hope those software problems have been resolved by now. • I usually use Google Chrome- but for some reason Canvas and Google Chrome don't mesh very well.
		Questions & answering on quizzes/exams/assignment clarification (e.g., assignment due)		• This quiz was pretty representative of what we covered in the homework. • When is Midterm 2 due? My canvas says it's due tomorrow?

CURRICULUM VITAE

JI EUN LEE

Department of Instructional Technology and Learning Sciences
Utah State University
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EDUCATION

Ph.D. in Instructional Technology and Learning Sciences **Summer 2019**
Utah State University, Logan, UT

- Dissertation: *The effects of discussion strategies and learner interactions on performance in online mathematics courses: An application of learning analytics*
- Committee: Mimi Recker (Chair), Andy Walker, Jody Clarke-Midura, Daniel Coster, Yong Seog Kim

M.A. in Educational Technology **2010**
Ewha Woman's University, Seoul, South Korea

- Thesis: *Identifying the predictors of learning outcomes in using digital mathematics textbooks*
- Committee: Myunghee Kang (Chair), Il-Hyun Jo, Jeongmin Lee

B.A. in Home Economics Education · Mass Communications **2006**
Korea University, Seoul, South Korea (graduated Magna Cum Laude)

RESEARCH INTERESTS

Learning analytics; Computer Supported Collaborative Learning (CSCL); Online learning environments; Analysis of learner interaction and discourse patterns; Automated content analysis, Natural Language Processing (NLP); Text mining

PUBLICATIONS

PEER-REVIEWED JOURNAL ARTICLES

Lee, J. E., & Recker, M. (2019). Students' online discussion patterns, emotions, content and learning outcomes in an online developmental mathematics course. Accepted with minor revisions for the *Technology, Knowledge, and Learning*.

Lee, J. E., Recker, M., Choi, H., Hong, W. J., Kim, N. J., Lee, K., Lefler, M., Louviere, J., & Walker, A. (2015). Applying data mining methods to understand user interactions within learning management systems: Approaches and lessons

learned. *Journal of Educational Technology Development and Exchange, 8*(2), 99-116.

Kang, M., **Lee, J, E.**, Kim, M., & Yoon, N. (2011). Identifying the predictors of learning outcomes in using digital mathematics textbooks. *The Korean Journal of Educational Methodology Studies, 23*(1), 127-150. **[Master's Thesis]**

Kang, M., Song, Y. H., **Lee. J. E**., & Koo, J. (2010). Identifying the predictor variables of the learning outcomes in using English digital textbooks. *The Korean Journal of Educational Information and Media, 16*(2), 197-221.

PEER-REVIEWED BOOK CHAPTERS

Lee, J. E., & Recker, M. (2018). What studies of learning analytics reveal about learning and instruction: A systematic literature review. In J. M. Spector, B. B. Lockee & M. D. Childress (Eds.)., *Learning, design, and technology: An international compendium of theory, research, practice, and policy* (pp. 1 – 37). Cham, Switzerland: Springer International Publishing.

Recker, M. & **Lee, J. E.** (2016). Analyzing learner and instructor interactions within learning management systems: A review of approaches. In J. M. Spector, B. B. Lockee & M. D. Childress (Eds.)., *Learning, design, and technology. An international compendium of theory, research, practice, and policy* (pp. 1-23). Cham, Switzerland: Springer International Publishing.

MANUSCRIPTS UNDER REVIEW

Lee, J. E., Recker, M., & Yuan, M. (in review). The validity, reliability, and instructional value of a rubric for evaluating online course quality: An empirical study. Under review for the *Online Learning Journal*.

PAPERS IN PEER-REVIEWED CONFERENCE PROCEEDINGS

Lee, J. E. (2019). The effects of discussion strategies and learner interactions on performance in online mathematics courses: An application of learning analytics. In D. Azcona & R. Chung (Eds.), *Companion Proceedings of the 9th International Learning Analytics & Knowledge (LAK) Conference.* Tempe, AZ: Society for Learning Analytics Research.

Lee, J. E., Recker, M., Bowers, A. J., & Yuan, M. (2016). Hierarchical cluster analysis heatmaps and pattern analysis: An approach for visualizing learning management system interaction data. In T. Barnes, M. Chi & M. Feng (Eds.), *Proceedings of the 9th International Conference on Educational Data Mining* (pp. 603-604). New York, NY: ACM.

Choi, H., **Lee, J. E**., Hong, W. J., Lee, K., Recker, M., & Walker, A. (2016). Exploring

learning management system interaction data: Combining data-driven and theory-driven approaches. In T. Barnes, M. Chi & M. Feng (Eds.), *Proceedings of the 9th International Conference on Educational Data Mining* (pp. 324-329). New York, NY: ACM.

Jung, H. Y., Park, M., Lee, J., **Lee, J. E**., & Han, J. S. (2010). Are boys and girls really that different: New millennium learners' educational performance. *Proceedings of the IADIS International Conference on e-Learning*, Freiburg, Germany.

Kang, M., Jo, I., Park, M., Lee, S., Jung, H. Y., **Lee, J. E**., & Kang, W. (2009). Developing an educational performance indicator for new millennium learners. *Proceedings of Cognition and Exploratory Learning in Digital Age* (pp. 101-109). Rome, Italy: IADIS Publications.

TECHNICAL REPORTS / WHITE PAPERS

Lee, J. E. & Recker, M. (2017). Examining students' self-regulated learning strategies using learning management system data: An evidence-centered design approach. *Measurement in Digital Environments White Paper Series*. Menlo Park, CA: SRI International.

UNESCO Bangkok. (2011). *Information policies in Asia: Development of indicators*. Bangkok, Thailand: UNESCO Office Bangkok and Regional Bureau for Education in Asia and the Pacific. (*Wrote the 2nd part of the report, Implementing the indicators: Examples of measurement and questionnaire (pp. 58-89). Available at http://unesdoc.unesco.org/images/0020/002070/207048e.pdf

CONFERENCE PRESENTATIONS

Lee, J. E., Recker, M., & Yuan, M. (2019, April). *Examining the validity and instructional value of a rubric for evaluating online course quality*. Poster presented at the annual meeting of the American Educational Research Association (AERA), Toronto, Canada.

Lee, J. E. (2019, March). *The effects of discussion strategies and learner interactions on performance in online mathematics courses: An application of learning analytics*. Poster presented at 9th International Conference on Learning Analytics & Knowledge (LAK), Tempe, Arizona.

Lee, J, E., & Recker, M. (2018, April). *Exploring relationships between students' discussion patterns, emotions and learning outcomes in an online mathematics course*. Paper presented at the annual meeting of the American Educational Research Association (AERA), New York, NY.

Lee, J, E., & Recker, M. (2018, April). *Exploring relationships between student online usage patterns and learning outcomes in developmental mathematics courses*. Poster presented at the annual meeting of the American Educational Research

Association (AERA), New York, NY.

Lee, J, E., & Recker, M. (2017, April). *Examining students' self-regulated learning strategies using learning management system data: An evidence-centered design approach.* Paper presented at the annual meeting of the American Educational Research Association (AERA), San Antonio, TX. **[Awarded SIG-Advanced Technologies for Learning/Learning Sciences Best Student Paper]**

Lee, J, E., & Recker, M. (2016, October). *The validity, reliability, and utility of a rubric for evaluating online course quality: An empirical study*. Paper presented at the Association for Educational Communications and Technology (AECT) International Convention, Las Vegas, NV.

Choi, H., **Lee, J. E**., Hong, W. J., Lee, K., Recker, M., & Walker, A. (2016, June). *Exploring learning management system interaction data: Combining data-driven and theory-driven approaches*. Paper presented at the 9th International Conference on Educational Data Mining, Raleigh, NC.

Lee, J. E., Recker, M., Bowers, A. J., & Yuan, M. (2016, June). *Hierarchical cluster analysis heatmaps and pattern analysis: An approach for visualizing learning management system interaction data*. Poster presented at the 9th International Conference on Educational Data Mining, Raleigh, NC.

Lee, J. E., & Clarke-Midura, J. (2016, April). *Using a massively multiplayer online game to teach evolution*. Poster presented at the annual meeting of the American Educational Research Association (AERA), Washington, DC.

Choi, H., Hong, W. J., Kim, N. J., **Lee, J. E**., Lee, K., Lefler, M., Louviere, J., Recker, M., & Walker, M. (2016, April). *Applying data mining methods to understand user interactions within learning management systems: Approaches and lessons learned*. Paper presented at the annual meeting of American Educational Research Association (AERA), Washington, DC.

Lee, J. E., & Yoon, N. R. (2010, December). *Identifying predictor variables of the learning outcomes in using digital mathematics textbook.* Paper presented at the 2nd East Asian International Conference on Teacher Education Research, Hongkong, China.

RESEARCH EXPERIENCE

Graduate Research Assistant August 2014 – May 2019

***Department of Instructional Technology and Learning Sciences, Utah State University**, Logan, UT*

2014 – 2019 | Research Assistant to Dr. Mimi Recker

- **Canvalytics project: Understanding interaction data from the Canvas Learning Management System**: Conducted a literature review, data-preprocessing (data extraction and cleaning), data mining (classification, prediction, visualization, text mining) and quantitative analyses to predict student performance in online courses using the clickstream and textual data collected by the Canvas Learning Management System. Assisted in writing a grant proposal.
- **SchoolWide Labs project: A real-time sensing platform for integrating computational thinking into middle school STEM curricula** [NSF funded project]: Assisted in the evaluation of the research project (Research Practice Partnership)
- **Course Design Assistant**: eLearning Trends and Issues [ITLS 5150/6150]: Assisted in the design, development, and facilitation of the online course

2015 | Research Assistant to Dr. Jody Clarke-Midura

- Radix project: Conducted a literature review, data pre-processing (cleaning, transformation, organization) and performed quantitative analyses using the data collected by the Radix Endeavor, a Massively Multiplayer Online Game (MMOG) with Science, Technology, Engineering and Mathematics (STEM) topics for middle and high school curriculum

Research Assistant November 2013 – March 2014

***Department of Computer Science Education, Korea University**, Seoul, South Korea*

- Assisted in the research project (literature review and paper writing) on the development of the platform and generic technology for adaptive publication and open market service in social media environments

Researcher July 2012 - October 2013

***Center for Teaching Learning, Korea University**, Seoul, South Korea*

- Responsible for the overall management, design, implementation, and evaluation of the Learning Management System (LMS), e-learning programs and tools
- Provided training and workshops for faculty, TAs, and students related to the use of the LMS, e-learning tools/programs
- Conducted research on undergraduate students' ICT use.

Assistant Researcher April 2011 - June 2012

***Korean Educational Development Institution (KEDI),** Seoul, South Korea*

- Engaged in a nation-wide research project (literature review, quantitative analyses, paper writing) on developing indicators of school crime and safety

Intern September 2010 - February 2011

***UNESCO Asia-Pacific Regional Bureau for Education**, Bangkok, Thailand*

- Assisted in the research (literature review and paper writing) on the development of indicators on ICT use for Asia and the Pacific region
- Assisted in organizing and preparing international meetings and workshops on education, ICT use, and information literacy

Graduate Research Assistant March 2009 - July 2010

***Department of Educational Technology, Ewha Woman's University**, Seoul, South Korea*

- Assisted the research project with Electronics and Telecommunications Research Institute (ETRI) on developing a collaborative learning model for ubiquitous learning environments

Graduate Assistant September 2008 - February 2009

***Institute for Teaching & Learning, Ewha Woman's University**, Seoul, South Korea*

- Engaged in creating and evaluating online learning contents/materials
- Served as a Teaching Assistant in a blended science course with Pohang University of Science and Technology

PROFESSIONAL EXPERIENCE

Instructional Designer (Temporary position) July – August 2010

***Samsung SDS Co., Ltd**. Seoul, South Korea*

Corporate Planner January 2006 - May 2008

***Eugene Corporation**, Seoul, South Korea*

Intern June - December 2005

***Tooniverse, ON Media Co., Ltd**. Seoul, South Korea*

Trainee Teacher (Home Economics) April 2005

***Hwagye Middle School**, Seoul, South Korea*

AWARDS / HONORS

Doctoral Student Researcher of the Year March 2019

Instructional Technology & Learning Sciences Department, Utah State University

Learning Analytics & Knowledge (LAK 19) Doctoral Consortium March 2019

Society for Learning Analytics Research

Data Consortium Fellowships 2018 August 2018
The Data Consortium Fellows (DCF) program

Graduate Research and Creative Opportunities (GRCO) August 2018
Office of Research and Graduate Studies, Utah State University

Best Student Paper Award April 2017
American Educational Research Association (AERA) SIG-Advanced Technologies for Learning/Learning Sciences

Presidential Doctoral Research Fellowship Fall 2015 – Spring 2019
Office of Research and Graduate Studies, Utah State University

Graduate Research Assistantship Fall 2014 – Spring 2015
Instructional Technology & Learning Sciences Department, Utah State University

Global Internship Scholarship 2010
National Research Foundation of Korea.

Research Assistant Scholarship Fall 2010
Department of Educational Technology, Ewha Woman's University.

BK21(Brain Korea 21) Scholarship Spring - Fall 2009
Department of Educational Technology, Ewha Woman's University.

Student Assistant Scholarship Fall 2008
Institute for Teaching & Learning, Ewha Woman's University.

Great Honor (awarded for academic excellence) February 2006
College of Education, Korea University.

Honors Scholarship (awarded for academic excellence) Spring 2003, Spring-Fall 2005
College of Education, Korea University.

Semester High Honors (awarded for academic excellence)
Fall 2001, Spring 2002, Fall 2004, Spring-Fall 2005
College of Education, Korea University.

Freshman Special Scholarship (awarded for academic excellence) Spring 2001
College of Education, Korea University.

STATISTICAL / TECHNICAL SKILLS

- Data analysis: R programming, SAS, SPSS, Mplus
- Data pre-processing: SQL Server Management Studio
- Data visualization & Social network analysis: Tableau, Gephi
- Text mining: LightSIDE, KH Coder, LIWC
- Other: HTML

WORKSHOP PARTICIPATION

Data Consortium Fellowship (DCF) 2018 meeting August 16-17, 2018
The Data Consortium Fellows (DCF) program and Twin Cities PBS (TPT), St. Paul, MN

Simon Initiative LearnLab Summer School (EDM Track) July 10-14, 2017
Carnegie Mellon University, Pittsburgh, PA

Deep Multimodal Data Jam April, 2015
Learning Games Play Data Consortium and Analytics4Learning, Chicago, IL

SERVICE / PROFESSIONAL MEMBERSHIP

2019 Reviewer, Journal of Applied Research in Higher Education (JARHE)

2019 Member, Society for Learning Analytics Research (SoLAR)

2016 Member, Association for Educational Communications and Technology (AECT)

2014 – present Member, American Educational Research Association (AERA)

CERTIFICATES

- Certificate of Completion (2017). Simon Initiative LearnLab Summer School (Educational Data Mining Track), Carnegie Mellon University
- Completion certificate of e-learning quality assurance specialist training (2012). Korea Education and Research Information Service (KERIS).
- Participation and presentation certification at the IADIS International Conference CELDA, Rome, Italy, (2009). International Association for Development of the Information Society (IADIS).
- Regular teacher certification as a home economics teacher (2006). Korean Ministry of Education.

MORE INFORMATION

- Google Scholar: https://tinyurl.com/y2vodqrm
- ResearchGate: https://tinyurl.com/y3kad6ef