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Interaction, Internet Self-Efficacy, and Self-Regulated Learning as Predictors of Student Satisfaction in Distance Education Courses

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INTERACTION, INTERNET SELF-EFFICACY, AND SELF-REGULATED LEARNING AS PREDICTORS OF STUDENT SATISFACTION IN DISTANCE EDUCATION COURSES

by

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ABSTRACT

Interaction, Internet Self-Efficacy, and Self-Regulated
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Online learning research is largely devoted to comparisons of the learning gains between face-to-face and distance students. While student learning is important, comparatively little is known about student satisfaction when engaged in online learning and what contributes to or promotes student satisfaction. Emerging research suggests there are a few strong predictors of student satisfaction, and other predictors that may or may not predict student satisfaction. None of the existing research examines predictors together, or statistically controls for course differences. This study examines the influence of various factors on student satisfaction including three types of interaction, Internet self-efficacy, and self-regulated learning.

Participants ($N = 180$) include both undergraduate and graduate students attending exclusively online classes in education. Students responded to an online survey adapted from several different scales. A pilot test of the survey and procedures showed strong validity and reliability for the sample. To control for course differences, data analysis focused on a hierarchical linear model (HLM) with student and class level variables. Results indicate learner-instructor interaction and learner-content interaction are significant predictors of student satisfaction when class-level variables are excluded. Of the class-level predictors, only the program from which the course was offered moderates the effect of learner-content interaction on student satisfaction. There is no direct impact of class-level predictors on student satisfaction. Learner-content interaction is the sole significant predictor when class-level predictors are added to the model. Supporting analyses for the HLM, results, limitations, and significance of the findings are reported and discussed.

(157 pages)

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Yu-Chun Kuo

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CHAPTER I

INTRODUCTION

Distance learning is becoming mainstream alongside the rapid dissemination of computer technologies and improvements in Internet infrastructure (Allen & Seaman, 2008; Parsad & Lewis, 2008). Previous research on distance education concentrated on the comparison of learning outcomes between distance learning and traditional classroom learning, and most studies found no significant differences in learning outcomes between them (Allen, Bourhis, Burrell, & Mabry, 2002; Biner, Bink, Huffman, & Dean, 1997; Brown & Liedholm, 2002; Johnson, Aragon, Shaik, & Palma-Rivas, 2000).

Student satisfaction, which reflects how students perceive their learning experiences, is an important measure in program evaluation. Students with a higher level of satisfaction are more persistent in their learning, and research evidence suggests that providing students a satisfying experience helps to maintain and improve retention (Debourgh, 1999; Koseke & Koseke, 1991). In addition, student satisfaction contributes to academic achievement. The more students are satisfied, the more likely they are to do well in the course (Keller, 1983; Pike, 1993).

Several studies investigated the factors that contribute to student satisfaction in distance learning environments (Artino, 2007; Bolliger & Martindale, 2004; Reinhart & Schneider, 2001; Sahin, 2007). Based on that work, factors such as interaction, Internet self-efficacy and self-regulated learning are consistently examined as predictors of student satisfaction. Some studies indicate that interaction is a predictor for satisfaction in online or web-based learning environments (Bray, Aoki, & Dlugosh, 2008; Chejlyk, 2006; Keeler, 2006; Rodriguez Robles, 2006). Only two studies investigated the relationship between Internet self-efficacy and satisfaction, and both of them showed that Internet self-efficacy is not significantly correlated with or predictive of satisfaction (Puzziferro, 2006; Rodriguez Robles, 2006). Only two studies examined the relationship between self-regulated learning and satisfaction, both of which showed a significantly positive correlation (Artino, 2007; Puzziferro, 2008). Given the low volume of studies replication, work is needed to assess the relationships between Internet self-efficacy, self-regulation, and student satisfaction in online learning. Exact replication work may not be enough. Internet self-efficacy and self-regulation are typically used as sole predictors of student satisfaction (Artino, 2007; Puzziferro, 2008; Rodriguez Robles, 2006). Few studies are available that examine both Internet self-efficacy and self-regulation simultaneously. No articles assess the relationships between interaction, Internet self-efficacy, self-regulation, and student satisfaction. Finally, research in this area tends to treat students from different classes, with fundamentally different experiences, as coming from the same group. No advanced statistical techniques, such as hierarchical linear modeling (HLM) have been employed to adjust for group level differences.

Purpose and Objectives

The overall purpose of this study is to determine the factors that are associated with student satisfaction in online learning. In supporting this purpose, the primary objectives are twofold. The first objective is to investigate the relationships between and among learner-instructor interaction, learner-learner interaction, learner-content interaction, Internet self-efficacy, and self-regulated learning and student satisfaction. The second objective is to determine the extent to which student satisfaction can be accurately predicted. Finally, this study examines the unique contribution of key predictor variables in explaining the variation of student satisfaction scores, and explores the direct and moderator effects of class-level predictors on student satisfaction.

Research Questions

1. To what extent does each predictor variable (learner-instructor interaction, learner-learner interaction, learner-content interaction, Internet self-efficacy, and self-regulated learning) correlate with student satisfaction?

2. To what extent does the combination of interaction, Internet self-efficacy, and self-regulated learning predict student satisfaction?

3. Which of the variables remain significant when all are used to predict student satisfaction?

4. Of those variables that combine for the best prediction of student satisfaction, how much unique variance in student satisfaction does the significant predictor explain?

5. Do the class-level predictors (course category and program) affect student satisfaction and moderate the effects of three types of the interaction, self-regulated learning, and Internet self-efficacy variables on student satisfaction?

Definition of Terms

Communication

Communication refers to a process by which individuals exchange information or share meaning with other people or individuals who receive or respond messages from each other through various technologies (Jonassen, Davidson, Collins, Campbell, & Haag, 1995).

Learner-Learner Interaction

Learner-learner interaction is a two-way reciprocal communication between or among learners who exchange information, knowledge, thoughts or ideas regarding course content, with or without the presence of an instructor (Moore & Kearsley, 1996). Learner-learner interaction is measured by a 5-point Likert scale of the level of interaction students reported experiencing with their peers. For example, exchanging ideas, providing feedback or comments, and collaborating on activities or projects through different types of technology. Learner-learner interaction is a predictor variable in this study.

Learner-Instructor Interaction

Learner-instructor interaction is a two-way communication between the instructor of the course and learners (Moore & Kearsley, 1996). Learner-instructor interaction is measured by a 5-point Likert scale of the level of interaction students reported experiencing with the instructor when they received feedback or comments, or had the chance to communicate with the instructor through a variety of electronic tools. Learner-instructor interaction is a predictor in this study.

Learner-Content Interaction

Learner-content interaction is a process of individual learners elaborating and reflecting on the subject matter or the course content. In contrast with learner-instructor and learner-learner interaction only one person, the learner, is directly involved (Moore & Kearsley, 1996). It is a predictor variable in this study, and is measured with a 5-point Likert scale assessing students' perceptions of (a) the ease of accessing online course content, (b) the relation between the course content and their previous experiences, and (c) the appeal of course content.

Internet Self-Efficacy

Internet self-efficacy is belief in one’s capability to organize and execute Internet actions required to produce given results (Eastin & LaRose, 2000, p.1). For instance, a person is asked to use the Internet to collect data or resources. Internet self-efficacy is a predictor variable and is measured by a 7-point Likert scale with 8 items regarding how confident the students are in working with Internet hardware and software, solving Internet problems, and learning advanced knowledge regarding the Internet.

Self-Regulated Learning

This study focused on Metacognitive self-regulation. Metacognitve strategies are those that students use to monitor or control their own cognition, such as goal planning or the monitoring of one’s comprehension (Pintrich, Smith, Garcia, &

McKeachie, 1993). Metacognitive self-regulation is measured by a 7-point Likert scale with 12 items regarding the extent to which students are able to plan, monitor, and regulate their learning. Metacognitive self-regulation is a predictor variable in this study.

CHAPTER II

REVIEW OF LITERATURE

The following section begins with a discussion of student satisfaction, the outcome variable for the predictive model. Following satisfaction, each predictive variable is introduced and discussed highlighting research into their relationships with or prediction of satisfaction in the existing literature. For all five components, the review focuses on their use in online learning settings. An underlying assumption of this research and the research cited in this review is the utility of self-report measures.

Self-report is a critical component of program evaluation (Gall, Gall, & Borg, 2007). Although the primary goal of this work is research and not evaluation, the resulting model may help inform key decisions by practitioners in distance education seeking to improve student satisfaction. Perhaps most importantly, Internet self-efficacy and satisfaction are fundamentally self-report constructs. Because they are self-report, consistent use of self-report is important to maintain congruence. For instance, the self-report for learner-instructor interaction may be more predictive of self-reported satisfaction than the actual amount of learner-instructor interaction. The intent of this work is to examine the relationships between these constructs, necessitating a large volume of quantifiable data. Self-report provides an efficient and scalable mechanism to provide the required data. Alternatives, such as observation or examination of learner-learner interactions would require an intrusive level of data collection, such as monitoring email or discussion boards. In addition, the results may arbitrarily ignore alternative modes of communication or improperly weight them due to accessibility of the data.

Learner perceptions towards independent and dependent variables might be moderated through such variables as course design, communication modes, asynchronous or synchronous formats, etc. Investigation on the extent to which independent variables have direct and moderating influence on student satisfaction brings contributions for future study. However, before getting there, information regarding the relationships between independent variables and student satisfaction is necessary. If there are no relationships between independent variables and student satisfaction, researchers do not need to go further and investigate the influence of that specific independent variable on student satisfaction and also the influence of potential moderators. This study is thus a first step in a much larger volume of future work.

Articles in the literature review were searched through EbscoHOST by using the single keywords such as interaction, self-regulated learning, self-efficacy, and satisfaction or the following combinations of keywords: (a) interaction plus online, web-based, and distance; (b) self-regulated or self-regulation plus online, web-based, and distance; (c) self-efficacy plus online, web-based, and distance; and (d) satisfaction plus online, web-based, and distance. EbscoHOST contains 53 databases, all selected by the researcher during article search. There were about 429 interaction-related articles including some duplicates. However, not all of them were included in this review. This study only selected the articles that contained types of interaction underlying Moore's model (1989). Articles covering strategic, informative or other forms of interaction were excluded. In addition, articles were selected that involved the conceptual introduction of self-regulated learning or investigated how self-regulation relates to satisfaction. Articles were also included if they broadly examined self-efficacy or focused on Internet self-efficacy. Articles related to computer self-efficacy were included, but were not the main focus in this study.

Satisfaction

A body of research in distance education has focused on the investigation of learning outcomes. Many of them examined cognitive learning outcomes, such as effectiveness of distance courses, student performance, or student achievement, each of which are usually measured in terms of course grades (Barnard, Paton, & Lan, 2008; Edvardsson & Oskarsson, 2008; Offir, Bezalel, & Barth, 2007; Wadsworth, Husman, Duggan, & Pennington, 2007). Affective perspectives were often neglected. Researchers have argued that students' attitudes are worthy of investigation and are found to be a good source of information about the quality of distance courses. Of these attitudinal constructs, student satisfaction should be taken into consideration. Student satisfaction is an important indicator of the effectiveness of a course and is critical to the success of distance programs (Allen & Seaman, 2003; Biner, Welsh, Barone, Summers, & Dean, 1997; Keller, 1987).

Studies of student satisfaction in online learning have attempted to determine the factors that influence student satisfaction. Findings from several studies indicate student satisfaction is related to a number of factors such as interaction, types of support, student autonomy, technology, self-efficacy, and self-regulation (Artino, 2007;

Bolliger & Martindale, 2004; Reinhart & Schneider, 2001; Sahin, 2007). Different combinations of these factors are examined to be correlated with or predictive of student satisfaction in online learning environments (Biner, Welsh et al., 1997; Reinhart & Schneider, 2001; Rodriguez Robles, 2006; Yukselturk & Yildirim, 2008). Of these factors, interaction, Internet self-efficacy, and self-regulated learning are the focus of this study. The combination of these three factors is assumed to be predictive of student satisfaction.

Students with high satisfaction are expected to be more persistent and successful in online learning compared to their counterparts with low satisfaction. That is, high satisfaction contributes to increased course completion rates as well as increases in students' commitment to learning and motivation to pursue additional online courses. Satisfied students are also more likely to recommend the course to others, which brings more students to online programs. Hence, student satisfaction is important information for online course designers, educators, and administrators, especially when institutions are trying to improve course quality to maintain or increase the retention of students (Reinhart & Schneider, 2001).

Various measures exist to assess student satisfaction. Biner, Welsh et al. (1997) utilized the Telecourse Evaluation Questionnaire (TEQ) developed by himself and other researchers as the primary measurement for student satisfaction. TEQ assesses satisfaction with respect to the instructor or instruction, technological aspects of the course, course management, at-site personnel, promptness of material delivery, support services, and out-of-class communication with the instructor. Lim (2001) developed an instrument for the measurement of satisfaction based on the exploration of adult learners' overall satisfaction of the web-based courses, and students' intent to participate in future web-based courses. Satisfaction in this study is defined as student's perception related to learning experiences and perceived value of a distance course. The measurement utilized in this study includes five items pertaining to an overall satisfaction students perceive towards the class, and the degree to which students perceive their learning experiences and interactions in a course. In addition, students' perceived contributions of this class to their professional or personal development and student willingness to take other online courses again are included.

Interaction

Interaction is a complex concept and has been deemed as one of the important ingredients in all forms of education, regardless of whether technology is involved. Interaction in traditional classroom learning focuses on the dialogues between instructors and students. Dewey (1916, 1938) described interaction as a component of the educational process where a transformation of the inert knowledge or information occurs, in terms of the transactional view where human factors and the environment are both taken into consideration. With the rapid development of emerging technologies, distance education has become an alternative to traditional face-to-face classroom learning. The concept of interaction has been expanded to distance learning environments within which a wide range of mediation takes place through different types of technology. Further, interaction is acknowledged as a pivotal factor for student success, satisfaction, and persistence in distance education (Bray et al., 2008).

Transactional Distance Theory

Transactional distance theory, developed by Moore (1989), describes interaction. Expanding on examination of physical separation alone, Moore postulated distance as a pedagogical phenomenon which involves the procedures taken by teachers, learners, and organizations to overcome the geographic distance. The concept of transaction originated from Dewey (1916), and it takes into account the interplay among the environments, the individuals, and the behaviors. Transactional distance exists in any educational events, including face-to-face environments as well as distance environments. If there is a learner, a teacher, and a communication channel, then some transactional distance exists. *Dialogue* and *structure* are two important components in transactional distance, which are used to determine the distance between students and teachers (Moore & Kearsley, 1996).

Dialogue refers to the interactions between the teacher and learners. The design of the course, the personalities of teachers and learners, language, and the medium of communication are possible factors that would influence the extent of dialogue. For instance, in an independent study or an audio-conference course, a highly dialogic process exists. Course structure includes such elements as learning objectives, content themes, information, exercises, and activities, which are usually organized by the instructor and impacts the ability to make adaptations. High structure leads to lower flexibility and lower flexibility makes individual adaptations less possible (Moore & Kearsley, 1996).

As indicated above, dialogue and structure are two components that are used to measure transactional distance. The degree of transactional distance varies from course to course. There will be less transactional distance if there is more dialogue and less structure. More transactional distance implies less dialogue between the instructor and learners. Generally, more responsibility will be assumed by learners in a course with greater transactional distance. When a course has less dialogue or structure, learners need to make their own decisions about what and how to study. (Moore & Kearsley, 1996; Vrasidas & McIsaac, 1999).

Definitions of Interaction

Interaction is highly emphasized in the existing literature due to the independence created by the temporal or geographical separation in distance learning environments. Typically, the quality of interaction occurring in a traditional classroom may not be obtained and the effectiveness of teaching and learning might be lowered to a certain degree. The most highly cited framework of interaction in distance education is proposed by Moore (1989), in which three major constituents are included: learner-instructor interaction, learner-learner interaction, and learner-content interaction. Garrison and Shale (1990) described all forms of education, including education at a distance, as interactions among teachers, students, and content, which take both human to human and human to content interactions into account. Also within distance contexts, Wagner (1994) defined interactions as reciprocal communications in which at least two objects and two actions are required (Wagner, 1994), which is very similar to the definition by Simpson and Galbo (1986) that interaction is reciprocity in actions and responses in an infinite variety of relationships, including verbal and nonverbal, conscious and nonconscious, enduring and causal (Simpson & Galbo, 1986).

Hillman, Willis, and Cunawardena (1994) argued the previous discussions about interaction overlooked the role of technologies which mediate all forms of interactions to a certain degree, and added another type of interaction—*learner-interface interaction*—to Moore's three types of interactions. Learner-interface interaction is defined as the processes by which people operate tools for the completion of a task (Hillman et al., 1994). This type of interaction acts as an essential component to other forms of interactions whenever they occur in distance learning environments.

Northrup, Lee, and Burgess (2002) categorized interaction within online learning into four elements: content interaction, conversation and collaboration, meta-cognitive skills, and need for support. Anderson (2003), focusing on the social, pedagogical, and economic impact, extended this definition by proposing six types of interactions: teacher-teacher, teacher-content, and content-content, in addition to the three types of interactions developed by Moore. Muirhead and Juwah (2004) took into consideration the previous definitions and proposed that interaction is a dialogue or discourse or event that occurs between participants or objects through the synchronous or asynchronous mediation of responses, feedback, or technology (Muirhead & Juwah, 2004). In spite of many types of interaction that are continuously addressed by researchers from different perspectives, Moore’s interaction model still predominates and guides subsequent related research on interaction in distance learning environments (Bray et al., 2008; Moore, 1989; Northrup et al., 2002; Wanstreet, 2006). Hence, this study will adopt Moore’s three types of interaction.

Learner-Instructor Interaction

Learner-instructor interaction refers to a two-way communication between the instructor of the course and learners (Moore & Kearsley, 1996). This type of interaction is regarded as valuable by students and by many instructors. Learner-instructor interaction can take on many forms. Some of them are indirect, such as instructors designing a course to stimulate student interest in course content or increase motivation to learn. Evaluation is conducted by instructors to make sure learners are on track, and certain assistance, such as guidance, support, and encouragement, is available from instructors when necessary. Instructors are especially valuable when students are at the point of knowledge application (Moore, 1989).

Feedback is important in learner-instructor interaction. With feedback from students, instructors ensure student comprehension of course materials and receive information on their own performance in delivering course content. Feedback from instructors is vital to students’ achievement in the courses (Anderson, 2003; Belanger & Jordan, 2000). Students favor timely feedback from instructors. In contrast, a lack of immediate feedback brings about feelings of isolation and dissatisfaction (McIsaac, Blocher, Mahes, & Vrasidas, 1999; Yukselturk & Yildirim, 2008). Northrup et al.

(2002) confirmed the importance of instructor feedback to students and found it effective when provided as little as two times per week. Students who can easily communicate with their instructors are more satisfied with the learning compared to those having difficulties interacting with their instructors (Bray et al., 2008).

Learners in online environments report more course satisfaction when the support from their instructors matches with their expectations of communicating with their instructors. Maintaining frequency of contact, having a regular presence in class discussion spaces, and making expectations clear to learners are three practices suggested for instructors to adopt in enhancing learner-instructor interaction during online learning (Dennen, Darabi, & Smith, 2007). According to Heinemann (2007), learner-instructor interaction includes three realms: the organizational, the social, and the intellectual. These three realms of learner-instructor interaction were found to have an influence on both cognitive and affective learning outcomes in online learning environments. Although there has been work on the impacts of learner-instructor interaction on affective learning outcomes, work on the specific affective outcome, student satisfaction, is needed.

Learner-Learner Interaction

Learner-learner interaction involves a two-way reciprocal communication between or among learners, with or without the presence of an instructor. This type of interaction is extremely valuable and sometimes essential for learning. By interacting with their fellow students, students are able to exchange ideas and get feedback from each other simultaneously. Students' interest and motivation are raised when they are waiting for responses from peers. Interacting with peers brings students to a deeper sense of understanding, and increases their intellectual accomplishments. Students develop concepts in a nonlinear way by sharing ideas and individual experiences with peers. In addition, the communication among students exposes learners to other cultures and enriches their learning experiences. The availability of a group of students is invaluable especially at the point when knowledge is further applied (Anderson, 2003; Moore, 1989).

The lack of learner-learner interaction has been pointed out as a major problem in distance courses. Students feel isolated from others when they get fewer chances to work with other students on assignments or receive feedback from other students in distance learning (Belanger & Jordan, 2000). Forming collaborative groups is a good way to decrease student isolation and increase the communication among students. Collaborative experiences enhance student engagement in online learning and promote a sense of a learning community in which learners share common value or ideas and actively participate in their learning (Battalio, 2007). Group-based activities can promote student collaboration by utilizing a variety of synchronous and asynchronous tools, such as chat rooms, instant messaging tools, and discussion boards. However, when forced, too much interaction decreases student satisfaction. Students who are required to participate in group or team work sometimes show a lower level of course satisfaction in that they perceive the interaction with other students as busywork, which leads to frustration and overload (Berge, 1999; Northrup et al., 2002).

Some research has indicated that the increase of learner-learner interaction enhances student satisfaction with online learning (Anderson, 2003; Battalio, 2007; Jung, Choi, Lim, & Leem, 2002). The design of online collaborative learning may be helpful in providing a higher level of learner-learner interaction (Arbaugh & Benbunan-Fich, 2007). In contrast, some findings report that students who do not prefer their interaction with peers are more satisfied with online courses, or that learner-learner interaction does not play a vital role in student satisfaction (Bray et al., 2008).

Learner-Content Interaction

Compared to learner-instructor and learner-learner interaction, learner-content interaction is more abstract. According to Moore (1989), learner-content interaction refers to a one way process of learners elaborating and reflecting on the subject matter or the course content. Learners have to construct their own knowledge through a process of accommodating new information into previously existing cognitive structures. Changes to their cognitive structures then lead to changes in understanding and perspectives. The interaction of learners with the content initiates an *internal didactic conversation*, which happens when learners talk or think to themselves about the information, knowledge, or ideas gained as part of a course experience. Through an internal conversation learners cognitively elaborate, organize, and reflect on the new knowledge they have obtained by integrating previous knowledge. This process of intellectually interacting with content is a required process for education (Moore, 1989; Moore & Kearsley, 1996).

Compared to traditional classroom learning where lecture and text are primarily used, distance learning environments, especially online learning, offer a multitude of ways for learners to interact with the content through the facilitation of various technologies. Moore and Kearsley (1996) highlighted the importance of learner-content interaction in online learning environments because learners' behavior toward goals is, to certain degrees, changed by the specific technology utilized in class. Present technologies offer a wide variety of media alternatives for creating learner-content interaction. From Tuovinen's (2000) perspective, media can be classified into five categories: sound, text, graphic, video, and virtual reality. He argued that the combinations of sound with other media are less likely to produce cognitive overload in that sound and visual images are processed by different parts of the brain (Bishop & Cates, 2001).

Mason and Kaye (1990) also indicated the vital role that learner-content interaction plays, and that for effective learning to occur, learners should consciously interact with or operate on the learning materials or resources. Learner-content interaction is critical not only in terms of a learner's knowledge constructions, but plays an integral role in all forms of interaction. Carefully designed materials help to improve the interactions between the instructor and learners, and among learners.

Various forms of interaction have been recognized as important factors in promoting student satisfaction within distance learning environments (Bray et al., 2008; Burnett, 2001; Moore & Kearsley, 1996; Northrup et al., 2002; Thurmond & Wambach, 2004) although some disagreements persist. In most of the literature, learner-learner interaction and learner-instructor interaction are generally considered important for student satisfaction in distance courses. Some research indicates that learner-instructor interaction is the only required interaction in online learning and identifies learner-instructor interaction as the best predictor for course satisfaction (Battalio, 2007; Bolliger & Martindale, 2004; Thurmond, 2003). Some research shows that the amount of interaction among learners is more strongly related to and predictive of learner satisfaction than the amount of learner interaction with the instructor (Jung et al., 2002; Rodriguez Robles, 2006). It is clear that too much collaboration required in learner-learner interaction reduces student satisfaction (Berge, 1999; Bray et al., 2008). Hence, it is hard to conclude whether learner-instructor interaction or learner-learner interaction is the primary factor of student satisfaction in online learning.

Both learner-instructor interaction and learner-learner interaction enhance student interaction with content. That is, learner-content interaction interplays with leaner-instructor interaction and learner-learner interaction and then jointly influences learning outcomes (Kerka, 1996). Learner-content interaction is considered a good predictor, sometimes as the best predictor, of student satisfaction (Chejlyk, 2006; Keeler, 2006). It seems that there is no conclusive result as to which type of the three interactions best predicts student satisfaction.

For the purpose of this study, these three types of interaction will be modified and defined more narrowly to fit the conditions of this study, as opposed to the broad definition from Moore (1989). In this research, learner-learner interaction refers to the extent to which students perceive their interaction with other fellow students when sharing their ideas or thoughts with their fellow students, commenting on the ideas of other students, working on the same project or group activities together, and communicating with each other by using a variety of technological means. Learner-instructor interaction involves the degree to which learners perceive their interaction with the instructor by asking questions through various communication mechanisms, and the degree to which they perceive the feedback and encouragement from the instructor. Learner-content interaction is more complex and includes the degree of ease learners perceive their efforts in accessing online course materials, and the extent to which they perceive that online course materials bring them to a better understanding or stimulate their interest for the course. The extent to which online course materials relate students' previous experiences to new concepts is also examined as part of student interaction with content.

Self-Efficacy

Self-efficacy theory derives from psychology and presents a theoretical framework which accounts for human behavior changes from diverse modes of treatment (Bandura, 1977). The concept of self-efficacy refers to efficacy expectations which present one's convictions towards behaviors required to obtain certain outcomes and determine the effort people will make and how long they will persist when encountering obstacles or aversive experiences. Efficacy expectations are different from outcome expectations in which certain outcomes are expected given a specific behavior. People can believe a certain behavior brings specific outcomes, but they might have little confidence or faith in performing the action. Self-efficacy refers to one's belief in his or her capability to organize and implement actions necessary to attain designated performance for specific tasks (Bandura, 1997). It does not concern the actual ability or skills one has, but the judgments of the ability or skills that one thinks they possess; that is, the perceived self-efficacy which contributes to the acquisition of knowledge and development of skills (Bandura, 1986, 1997). The concept of self-efficacy has a long tradition and has been widely applied to social science related areas, such as learning, program evaluation, human resource management, innovation, and training (Torkzadeh & Van Dyke, 2002). Self-efficacy is context-specific and varies from situation to situation. Self-efficacy is dependent on the domain or the levels of task demands within which it is applied to, and can not be measured through an omnibus test (Hodges, 2008).

When it comes to educational contexts, self-efficacy has been popular in the investigation of performance or learning outcomes in academic environments, and is also called as academic self-efficacy, which concerns one's confidence in their successful performance in academic learning. Students' perceptions of self-efficacy in traditional classroom learning is found to have a positive influence on learning outcomes such as task persistence, task choice, skill acquisition, and academic achievement or performance (Hodges, 2008; Pintrich & De Groot, 1990). Generally, students with higher self-efficacy for completing a task are more likely to have higher motivation, make greater efforts, and persist longer than those with lower self-efficacy. High self-efficacy brings students to a deeper engagement of learning tasks and leads to better performance, which in turn continuously raises students' sense of self-efficacy. In contrast, low self-efficacy brings about inferior performance, and in turn decreases the sense of self-efficacy for a series of following relevant tasks (Bandura, 1977, 1982; Bandura & Schunk, 1981).

Self-Efficacy in Online Learning Environments

With the emergence of information technologies, various technological tools have been integrated into the process of learning, with corresponding effects on students' self-efficacy. Investigating the indirect influence of the integration of technological tools into learning is especially crucial in research related to Instructional Technology. As Hodges (2008) indicated, there is lack of research on motivation constructs in online learning environments. Concern for the affective domain is absent due to its difficulty in conceptualization and measurement, even though Dick, Carey, and Carey (2005) have identified motivation as an important factor that should be considered by instructors in course design. Hence, it is imperative to conduct more research on the relationship between self-efficacy and online learning.

According to Bandura (1977), performance accomplishments, vicarious experience, verbal persuasion, and emotional arousal are four sources of self-efficacy and can be applied in online learning as well. Depending on the structure of online courses, student self-efficacy is able to be manipulated by weighing each of them. Previous successful experiences enhance mastery expectations while repeated failure decreases them. Vicarious experience involves one's observation of others performing a task successfully or overcoming difficulties by exerting certain strategies. Verbal persuasion is widely used because of its ease of use and availability. Emotional arousal reveals physiological and affective states, such as stress, emotion, anxiety, and pain. High arousal weakens performance while a modest level of arousal raises attention and facilitates the use of skills (Bandura, 1977; Hodges, 2008).

Self-efficacy is a broad term, and it generally refers to three types of self-efficacy when it is extended to the domain of online learning. These three types of self-efficacy encompass self-efficacy for online learning, computer self-efficacy, and Internet self-efficacy. Most self-efficacy research in online learning environments has focused on either computer self-efficacy or Internet self-efficacy, but little research about self-efficacy for online learning has been conducted so far (Hodges, 2008).

Self-Efficacy for Online Learning

Self-efficacy for online learning is similar to the concept of academic self-efficacy, which is examined in traditional learning settings (Hodges, 2008). The difference is that self-efficacy for online learning focuses mainly on the context of online learning which is mediated by a variety of synchronous or asynchronous tools. It can be also described as academic self-efficacy in online contexts. Self-efficacy for online learning involves how confident online learners are in performing assigned learning tasks in technology-mediated environments. Technology, to a certain degree, plays a vital role towards the success of learning, depending on which types of deliveries are utilized, which doesn’t occur in traditional learning environments. That is, the influence of technology has been automatically taken into consideration when referring to self-efficacy for online learning. The correlation between self-efficacy for online learning and performance is mixed, with some showing a positive relationship of self-efficacy for online learning with performance (Wang & Newlin, 2002), and some indicating self-efficacy for online learning is not predictive of performance (Joo, Bong, & Choi, 2000; Lee & Witta, 2001). Concepts closely related to self-efficacy for online learning are computer self-efficacy and Internet self-efficacy.

Computer Self-Efficacy

The concept of self-efficacy helps to bring a better understanding of how new tools are adopted by individuals and how relevant use of those tools are developed. It is also helpful in making a better decision regarding technology implementation, acceptance, and use (Davis, 1989; Hedman & Sharafi, 2004; Papasratorn & Wangpipatwong, 2006; Shelton, Turns, & Wagner, 2002; Torkzadeh, Chang, & Demirhan, 2006; Torkzadeh & Van Dyke, 2002). Compeau and Higgins (1995) defined computer self-efficacy as “a judgment of one’s ability to use a computer” (p. 192). The concept of computer self-efficacy helps to better understand computer user behavior and system use. It has been indentified having an association with factors such as performance, satisfaction, user attitudes towards computer, computer experiences, frequency of computer usage, computer training, computer anxiety, and skills of information searching (Compeau & Higgins, 1995; DeTure, 2004; Hill & Hannafin, 1997; Lim, 2001; Osborn, 2001; Torkzadeh et al., 2006; Torkzadeh & Van

Dyke, 2002). Several scales have been designed for the measurement of computer self-efficacy. Generally, these scales are developed either for task-specific measures or for general measure (Compeau & Higgins, 1995; Murphy, Coover, & Owen, 1989; Torkzadeh et al., 2006).

Aligned with the belief that self-efficacy has been evidenced as a predictor of learning performance in traditional classroom learning, computer self-efficacy has a positive influence on performance in most online learning studies. Little research examines the effect of computer self-efficacy on satisfaction. Lim (2001) found that computer self-efficacy is a significant predictor of course satisfaction in a web-based distance course. Higher computer self-efficacy may enhance adult learners' confidence in their academic competence and may also result in a higher level of course satisfaction. Joo et al. (2000) found computer self-efficacy was a vital predictor of student success in online learning.

Internet Self-Efficacy

Internet self-efficacy refers to "the belief in one's capability to organize and execute Internet actions required to produce given attainments" (Eastin & LaRose, 2000, p. 1). Previous Internet experience is positively related to Internet self-efficacy (Eastin & LaRose, 2000). Males are generally found to have higher Internet skills than females. User attitude and computer anxiety are both found influential to Internet self-efficacy. People with high attitudes toward computers have higher Internet self-efficacy, compared to those with low attitudes toward computers. Training is helpful in the improvement of learners' Internet self-efficacy, especially for those with higher attitudes toward computers, and those with low computer anxiety. (Torkzadeh et al., 2006; Torkzadeh & Van Dyke, 2002).

Only two studies investigate the relationship between Internet self-efficacy and student satisfaction. Studies from Rodriguez Robles (2006) and Puzziferro (2008) showed that Internet self-efficacy is not predictive of student satisfaction in web-based learning environments. With the dearth of literature regarding student satisfaction, a wider net was cast. There is more research regarding the correlation between Internet self-efficacy and performance, which is in turn related to student satisfaction. Lim (2001) found that Internet experiences in a class have a positive correlation with student satisfaction. Both Joo et al. (2000) and Thompson, Meriac, and Cope (2002) pointed out that Internet self-efficacy positively predicted students' performance. Students with high Internet self-efficacy have better information searching skills and learn better than those with low Internet self-efficacy (Tsai & Tsai, 2003). On the other hand, some have found Internet self-efficacy is a poor predictor for student success in an online course (DeTure, 2004). Direct research examining the relationship between Internet self-efficacy and students satisfaction suggests there is no relationship, but the number of studies is small. Examinations of the relationship between Internet self-efficacy and student performance are mixed. More studies are needed to verify the correlation between Internet self-efficacy and student satisfaction.

This section describes three types of self-efficacy mentioned most often in online learning environments. Due to the rise of web-based learning courses that can be accessed through the Internet, possessing enough Internet-related ability or skills becomes more important, especially for online learners. Hence, this study will focus on Internet self-efficacy instead of computer self-efficacy, which involves the confidence of a person in using a computer.

Several measures for Internet self-efficacy exist. The Online Technologies Self-Efficacy Scale (OTSES) established by Miltiadou and Yu (2000) assesses online students' self-efficacy beliefs about communication technologies required for interaction and participation in an online course, such as email, Internet, and computer conferencing. The 30-item scale covers Internet competencies as well as synchronous and asynchronous interaction tools. Eastin and LaRose (2000) developed an eight-item measurement for Internet self-efficacy by distributing questionnaires to 171 undergraduates in an introductory communication class. Prior Internet experiences, outcome expectancies, Internet use, Internet stress, and self-disparagement are taken into account in the development of Internet self-efficacy. The Internet self-efficacy instrument developed by Torkzadeh and Van Dyke (2002) and Torkzadeh et al. (2006) mainly measures individual's self-perception and self-competency in interacting with the Internet. The 15 items are related to issues such as browsing, encryption, decryption, and system manipulation.

Research on the effect of Internet self-efficacy on certain learning outcomes is inconclusive, and the studies examining the relationship between Internet self-efficacy and satisfaction are very limited (Lee & Witta, 2001; Lim, 2001; Rodriguez Robles, 2006; Puzziferro, 2008). It is necessary to conduct more research to understand more about the influence of Internet self-efficacy on satisfaction in online learning.

Considering that previous examinations on Internet self-efficacy were so narrow and limited to specific task performance, this study will use the Internet self-efficacy scale developed by Eastin and LaRose (2000), which encompasses an overall measure related to general Internet use, with eight items regarding the extent to which people feel confident in understanding terms or words relevant to Internet hardware and software, describing functions of Internet hardware, solving Internet problems, gathering data through Internet, and learning Internet advanced skills.

Self-Regulated Learning

Self-regulation is originally from psychology and was defined by Bandura (1988) in terms of three forms of cognitive motivators including causal attributions, outcome expectancies, and cognized goals, each of which is based on its corresponding theory. Early self-regulation researchers were focusing on changing people's dysfunctional behaviors such as aggression, addiction, and some other behavior problems in a therapeutic world. Researchers now in education-related areas have gradually adopted the concept of self-regulation from psychology and adapted it to student learning or educational practice, which leads to the current concept of self-regulated learning (Schunk, 2005). These two terms self-regulation and self-regulated learning are interchangeable and have the same meaning in educational contexts.

The concept of self-regulated learning has been described by several researchers in different ways; however, the central idea underlying it is similar, which is about motivation and learning strategies that students utilize to achieve their learning goals. Based on Zimmerman (1989), self-regulated learning is defined as the degree to which students are metacognitively, motivationally, and behaviorally active participants in their own learning. A combination of cognitive, metacognitive, motivational and behavioral processes is needed in the pursuit of learning goals. Cognitive processes refer to the strategies that learners use to attain or comprehend knowledge or information. Metacognitive processes involve learners' ability to set up plans, schedules, or goals to monitor or evaluate their learning progress. Motivational processes indicate that learners are self-motivated and willing to take responsibility for their successes or failures. Behavior consists of seeking help from others to optimize learning (Zimmerman & Martinez-Pons, 1986, 1988). Self-regulated learning assumes a reciprocal causation among personal, behavioral, and environmental influence processes (Zimmerman, 1989).

Pintrich, a leading researcher in self-regulated learning, addresses self-regulation in terms of cognition, motivation, behavior, and context, in line with the definition of self-regulation from Zimmerman (1989). Pintrich and his colleagues have conducted self-regulated learning in educational contexts and contributed much to the formation of a conceptual framework of self-regulated learning as well as its application and effect in classroom learning (Schunk, 2005). Pintrich and De Groot (1990) highlighted the importance of motivation and presumed that merely utilizing cognitive and metacognitive strategies is not sufficient without taking into account individual differences in motivation which is assumed to be relevant to student cognitive and metacognitive engagement. According to their work, both motivational and self-regulated learning should be considered for successful academic achievement. Learners need to be motivated to employ the strategies as well as regulate their efforts.

Self-regulated learning has been recognized as one of the influential components of academic achievement in traditional classroom learning (Pintrich & De Groot, 1990; Zimmerman & Schunk, 1989). Most research shows that students willing to utilize as many self-regulated strategies as possible tend to succeed in their academic learning, more than their counterparts who use them less often. Moreover, self-regulated learners are more self-efficacious in learning than those with poor self-regulation skills. Self-regulated learners believe they can exert self-regulatory skills to help them learn efficiently. Successes are attributed to their personal competencies and effort, failures to the use of ineffective strategies or correctable causes. By way of contrast, low self-regulatory learners ascribe their failure to limited ability or insufficient effort (Schunk, 2005).

Self-Regulated Learning Model

A complete model of self-regulated learning and an associated instrument was not presented until 1993 (Pintrich et al., 1993). The model, which is an updated version with more detailed extensions of self-regulated learning components, includes two broad areas: motivation and learning strategies. Value, expectancy, and affect are three subareas proposed in the motivation construct, which is exactly an adaption from an expectancy value model of motivation. The motivation construct fits into the concept of forethought phase in the self-regulation cycle established by Zimmerman

(1998), in which forethought phase indicates the influential processes and beliefs, such as task analysis and self-motivational beliefs, before efforts are put into the stage of learning (Bothma & Monteith, 2004).

Expectancy refers to students' belief in the completion of a task, and includes two subcomponents, student perception of self-efficacy and control belief for learning. Value, showing the reason for a student to engage in a task, is measured based on three subscales: intrinsic goal orientation, extrinsic goal orientation, and task value beliefs. Intrinsic goals are about one's pursuit of something desirable to the individual. Extrinsic goals are about one's engagement in a task due to outside rewards or benefits, such as grades or approval from others. Task value beliefs refer to one's judgment about his or her interest in doing a task, or how useful or important the task is. The affect component is about student emotional reactions towards a task, such as student worry or concern for a task, and is measured by the test anxiety scale. (Pintrich & De Groot, 1990; Pintrich et al., 1993; Zimmerman, 1989).

The learning strategies construct encompasses three general types of scales: cognitive, metacognitive, and resource management strategies. Similar to Schunk's (2005) definitions of metacognitive and cognitive processes in self-directed learning, cognitive strategies focus on student use of strategies by which to process information or knowledge gained from lectures or textbooks. Metacognitve strategies involve the strategies that students use to monitor or control their own cognition, such as goal planning or the monitoring of one's comprehension. They are measured by two subscales: planning and monitoring. Resource management refers to one's ability to manage time, effort, or resources, and is measured by four subscales, which are time and study environment management, effort management, peer learning, and help-seeking (Pintrich et al., 1993). The learning strategies construct is aligned with performance or volitional control phase and self-reflection phase in a three-step self-regulation cycle proposed by Zimmerman (1998).

Self-Regulation in Online Learning Contexts

Compared to traditional classroom learning, which is usually considered more teacher-centered, online learning is more student-centered and students assume more responsibilities, especially in asynchronous learning environments. Distance learners often have less guidance and assistance from instructor or peers. In light of the characteristics of online learning such as flexibility, demands of more student efforts, and learner-centeredness, it is presumed that the ability of utilizing self-regulatory skills to set up learning goals, monitor their learning progress, seek help when needed and manage the time is of importance and necessary especially to distance learners (Bothma & Monteith, 2004; Jonassen et al., 1995; King, Harner, & Brown, 2000). That is, distance learners, to an even greater extent than traditional classroom learners, need to be active participants and control their learning in an efficient fashion by employing well-developed self-regulatory skills comprised of psychological processes and related learning strategies to be successful in learning (Artino, 2007). Students' ability to self-monitor and self-evaluate at different stages during the learning process, and to mange their study time effectively, plays an important role in the completion of distance courses. Students who are not able to keep up with the learning schedule or manage their own learning processes effectively usually end up failing the class. Dembo, Junge, and Lynch (2006) pointed out that self-regulatory skills can be taught before a distance course starts, or by embedding the skills within the course (Chang, 2005; Cho, 2004).

The influence of self-regulation in online learning environments has been demonstrated in recent studies. Most of these studies focused on the effect of self-regulation on student achievement or performance and revealed that self-regulated learning is positively related to achievement in online settings (Bell, 2006; Hargis, 2000; McManus, 2000; Shih & Gamon, 2001; Yukselturk & Bulut, 2005). However, very limited research focuses on how self-regulation is correlated with student satisfaction. Artino (2007) indicated task value and self-efficacy, which are two components in motivation construct of self-regulated learning, are significantly positive predictors of students' overall satisfaction with the online course. Rehearsal, elaboration, meta-cognitive self-regulation, time management, and study environment were determined to have significant positive correlations with the level of satisfaction in the study of Puzziferro (2008). Hence, it seems that more research is needed to verify the relationship between self-regulated learning and satisfaction.

This section describes the concept of self-regulation and its implications in online settings. As indicated, there is little research on the investigation of the influence of self-regulation on student satisfaction. More studies are needed to verify the relationship between self-regulated learning and satisfaction. Metacognitive strategies in self-regulation will be the focus in this study since metacognitive processes are considered as central in self-regulation (Brockett & Hiemstra, 1991; Corno, 1986; Corno & Mandinach, 1983).

This study will utilize the metacognitive self-regulation subscale in the Motivated Strategies for Learning Questionnaire (MSLQ), which is a 7-point Likert scale, as the measurement for self-regulated learning (Pintrich et al., 1993). This scale was selected for its validity, reliability, and alignment to the meta-cognitive portion of self-regulated learning. Metacognitive self-regulation involves the strategies that students use to control, monitor, and regulate cognition. It is measured by one subscale with 12 items in terms of planning, monitoring, and regulating.

Based on previous research, three types of interaction and self-regulated learning are often significantly correlated with student satisfaction. Table 5 shows the range of *r* square values for each independent variable according to former studies. The *r* square of Internet self-efficacy was almost zero, which reveals that Internet self-efficacy does not contribute to satisfaction. However, this was based on a limited number of studies and more work is needed.

CHAPTER III

METHODS

Design

This chapter describes the research design, sample, data collection, instruments, procedures, data analyses, and expected results. Given the general lack of information available, descriptive research is a necessary first step before meaningful interventions can be undertaken. The focus of descriptive research is on what is (Gall et al., 2007; Jonassen, 2004) rather than the examination of some intervention. This study relies on a correlational design (Campbell & Stanley, 1963) and seeks to explore relationships and then makes causal assertions. The primary research goal is to investigate the relationships between five variables (three types of interaction, Internet self-efficacy, and self-regulation) and student satisfaction in distance learning environments as well as the extent to which the five variables are predictive of student satisfaction. A pilot study was implemented in the summer of 2009. Although the procedures were tested as part of the pilot, the primary purpose was to examine the content validity and reliability of the interaction and student satisfaction subscales from the larger online survey instrument. The following sections outline the population and sample, data collection, instrumentation, and analyses from the pilot. After these sections, procedures for the full study which deviate from the pilot are specified.

Population and Sample

The target population will be generalized to online students from the Colleges of Education at land-grant public universities. The sampling frame was one of convenience, consisting of students enrolled in classes offered by the Emma Eccles Jones College of Education and Human Services (CEHS) at Utah State University.

Pilot Study

In order to obtain reliability information for the interaction and satisfaction subscales and to indentify the feasibility of data collection procedures, a pilot study was conducted in the summer of 2009. The summer-session courses lasted for 12 weeks, starting from mid-May to the end of July of 2009. Students enrolled in College of Education classes offered through distance education were recruited for participation. Students from a total of seven undergraduate and four graduate level courses received invitations to participate. To increase the response rate, a $100 dollar reward was given to one randomly selected participant.

With the assistance of the instructors, the online survey link was distributed to online students. Classes were drawn from five programs: (a) Family, Consumer, and Human Development; (b) Instructional Technology & Learning Sciences; (c) Communicative Disorders and Deaf Education; (d) Psychology; and (e) Special Education and Rehabilitation. The numbers of enrolled students and the course titles are listed in Appendix A. Of the 291 enrolled students from 11 online courses, 111 completed the online survey for the pilot study, a return rate of 38%.

Sample for the Full Study

The sampling frame for the full study was quite similar and consisted of undergraduate and graduate students attending classes offered by the College of Education in the Fall semester of 2009. The online courses were drawn from all seven programs of the College Education: (a) Instructional Technology and Learning Sciences; (b) Communicative Disorders and Deaf Education; (c) Family, Consumer, and Human Development; (d) Psychology; (e) Special Education and Rehabilitation; (f) School of Teacher Education and Leadership; and (g) Health, Physical Education, and Recreation.

Of the 990 enrollments from the courses with instructors' permission, there were 221 (22.32%) survey responses from the online students (Appendix G). This exceeds the minimum number of participants (N = 75) needed to test the regression model with five independent variables and allow for confident assumptions about observed relationships (Stevens, 2002).

Data Collection

Procedures for Pilot Study

The researcher contacted course instructors about their willingness to include their online students in this survey. A recruitment email (Appendix E) was sent out to all instructors who taught online courses offered through the College of Education. Instructors who were interested in this survey were asked to help pass on the online survey link to their students (Appendix F) by any mechanism that they normally used to contact their students (e.g., email, Blackboard announcements, Blackboard discussion threads, or some alternative means). The online survey was on SurveyMonkey. The survey was distributed in mid-July of 2009 for the pilot study.

Procedures for the Full Study

Similar data collection procedures tested in the pilot study were applied to the sample of this study collected from mid-November to mid-December of 2009, which was the end of Fall semester. Reminder messages regarding the online survey were sent through the instructors to increase student participation (Heberlein & Baumgartner, 1978).

Instrumentation

Data collection for the pilot study centered on a survey entitled Learner Interaction, Internet Self-Efficacy, Self-Regulated Learning and Satisfaction Survey (Appendix B). The survey included a set of demographics, five predictor variables: (a) learner-instructor interaction, (b) learner-learner interaction, (c) learner-content interaction), (d) Internet self-efficacy, and (e) self-regulated learning. It finished with the outcome variable of student satisfaction. Student background information encompassed the first five questions regarding gender, age, marital status, course level, and the hours spent online per week.

For the final-version survey, slight changes were made. The original question 4 in the demographics section of the online survey for pilot study was extended to three questions (Appendix D) for more detailed information on a specific online course. Considering that students might take multiple online courses at the same time, they were asked to indicate which class they were using as a basis for their survey responses, and provide information on course title, course number, and instructor name. Students were not allowed to fill out the survey multiple times if they were taking more than one online course from the College of Education in the Fall semester of 2009. Instead, students needed to select one course and filled out the survey based on that specific course experience. The subscales for the predictor variables and outcome were based on instruments referenced in the literature review above. Additional details follow. The measure of interaction was modified from prior research (Kuo, Eastmond, Schroder, & Bennett, 2009) related to student interaction and satisfaction in a blended distance learning course. This instrument was a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), and included three subscales. Based on a sample of 22 master students, reliability for each subscale as measured by Cronbach's alpha was quite strong for all three subscales including learner-learner interaction (11 items; alpha = 0.81), learner-instructor interaction (10 items, alpha = 0.80), and learner-content interaction (6 items, alpha = 0.90). The total reliability coefficient for all these three types of interactions was 0.85.

Slight modifications including wording changes were made to assure the suitability of items for this study before a content validity survey was conducted. In both leaner-learner interaction and learner-instructor interaction subscales, the phrase *instructor-led sessions* was changed to *during the class*. Communication tools such as Wimba, Blackboard chat rooms, MSN, skype, and Yahoo Messenger were added to item 2 in learner-learner interaction subscale and item 3 in learner-instructor interaction subscale separately. *Interactions* in item 1 of the learner-learner interaction subscale was specified to the course content. *Class presentation* in item 11 of the learner-learner interaction subscale was changed to *class projects*. There was no change in learner-content interaction subscale.

To assess the validity of the instrument, a survey was distributed to six experts. These six experts are professors with either research expertise in online learning, experience teaching online classes, or both. Each expert was asked to rate each item (Appendix C) and determine if the item is adequate for these specific domains, such as learner-learner interaction, learner-instructor interaction, and learner-content interaction. For each item, one of three choices can be selected: essential, useful but not essential, and neither essential nor useful. Content validity ratio (CVR) was calculated based on the ratings from these six experts (Cohen & Swerdlik, 2004).

Figure 3-1 shows the calculated CVR value of each item in the interaction scale. Considering the small number of experts, this research combined the number of experts indicating items as *essential* or *useful but not essential* for CVR calculation. According to the standard of CVR for the case of six experts, items with CVR value smaller than 0.99 should be deleted. However, some items with CVR lower than 0.99 were not eliminated; instead, slight wording changes were made based on the feedback from the experts, and then these slightly revised items were sent back to the experts who rated them as *neither essential nor useful* for a second-round rating. Items that were rated as essential or useful but not essential through the second-round rating were maintained in the survey. Items 2, 4, 5, and 6 in the learner-learner

No.	Items	CVR	Decision
Learner-learner interaction			
1	Overall, I had numerous interactions related to the course content with fellow students.	1.00	kept
2	I usually communicated with my classmates through instant messaging tools, such as Wimba, Blackboard chat rooms, MSN, Skype, Yahoo Messenger, etc.	0.67	combined with item 4, 5 & 6
3	I got lots of feedback from my classmates.	1.00	kept
4	Online discussion boards gave me opportunities to communicate with my fellow students.	1.00	combined with item 2
5	I usually interacted with my classmates through email.	0.33	
6	I usually got feedback from my classmates through the discussion board on Blackboard.	0.67	
7	I usually answered questions of my classmates through the discussion board.	1.00	kept
8	I often shared my thoughts or ideas about the lectures and its application with other students during this class.	0.67	kept (in the second-round rating: CVR = 1.00)
9	I often commented on other students' thoughts and ideas.	1.00	kept
10	Group activities during class gave me chances to interact with my classmates.	1.00	kept
11	Class projects led to interactions with my classmates.	1.00	kept
Learner-instructor interaction			
12	I had numerous interactions with the instructor during the class.	1.00	kept

Figure 3-1. CVR value of each item in the interaction scale.

No.	Items	CVR	Decision
13	I usually e-mailed the instructor with the questions that I had.	1.00	combined
14	I usually asked the instructor my questions through instant messaging tools, such as Wimba, Blackboard chat rooms, MSN, Skype, Yahoo Messenger, etc.	1.00	
15	I usually asked the instructor my questions through the discussion board.	1.00	
16	The instructor regularly posted some questions for students to discuss on the discussion board.	1.00	kept
17	The instructor often replied to my questions in a timely fashion.	1.00	kept
18	I often replied to messages from the instructor.	1.00	kept
19	I received enough feedback from my instructor when I needed it.	1.00	kept
20	The instructor encouraged us to question different ideas and perspectives.	0.33	removed
21	The instructor aroused my interest in some issues, which motivated me to learn more.	0.67	removed
Learner-content interaction			
22	Online course materials helped me to understand better the class content.	1.00	kept
23	Online course materials stimulated my interest for this course.	1.00	kept
24	Online course materials helped relate my personal experience to new concepts or new knowledge.	1.00	kept
25	I spent lots of time going over the course materials.	0.33	removed
26	I often looked at other online resources as a supplement to the course materials.	0.33	removed
27	It was easy for me to access the online course materials.	1.00	kept

Figure 3-1. Continued.

interaction subscale and items 13, 14, and 15 in the learner-instructor interaction subscale were combined into one item since they all intended to measure communications among students. The word *lectures* in item 8 of the learner-learner interaction subscale was replaced by *course content*. Excluded were item 20 and 21 in the learner-instructor interaction subscale, and item 25 and 26 in the learner-content interaction subscale.

Based on the suggestions of experts, words such as usually, often, better, and lots of were removed from several items. After item elimination and revision, there were 8 items in the learner-learner interaction subscale, 6 items in the learner-instructor interaction subscale, and 4 items in the learner-content interaction subscale (Appendix B). The Cronbach's coefficient alpha values calculated based on the sample of a pilot study (n =111) for learner-learner interaction (0.99), learner-instructor (0.88), and learner-content (0.93) interaction were all quite high.

The Internet self-efficacy scale with eight items developed by Eastin and LaRose (2000) to measure one's belief in performing Internet-based technology was used in this study. This measurement was a 7-point scale that ranged from 1 (very unlikely) to 7 (very likely). This scale was found to be reliable and internally consistent with a Cronbach's coefficient alpha value at 0.93, based on a population of 171 undergraduate students at a university. Construct validity of this scale was examined and established during prior instrument design efforts.

The self-regulated learning scale used in this study was adopted from the Metacognitive self-regulation subscale in the MSLQ developed by Pintrich et al.

(1993). The MSLQ was administered to a sample of 380 college students from 37 classrooms and 5 disciplines. MSLQ, including 15 subscales, has both validity as well as good reliability in terms of internal consistency. The metacognitive self-regulation subscale, which assesses the extent to which the planning, monitoring, and regulating strategies learners utilized during learning, is a 7-point Likert scale with 12 items ranging from 1 (not at all true of me) to 7 (very true of me). Planning is measured by student responses to the items regarding the degree to which students are able to set up goals for the course and skim the course content to see how it is organized before reading new course materials. Monitoring is assessed by items concerning the degree to which students are able to ask themselves questions to make sure they understand the course materials, and evaluate their learning progress by indicating the important concepts they do not understand. Regulating is measured by student responses to the items regarding the degree to which students are able to adjust their learning speed depending on the level of difficulty of the course content, and change the way of reading to achieve a better understanding of the course materials, as well as the way of studying based on the requirements of the course and the teaching style of the instructor. The coefficient alpha of Metacognitive for the self-regulation subscale was 0.79.

Student satisfaction was adapted from the instrument used in the same study noted above (Kuo et al., 2009). This satisfaction instrument included five items on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The scale was distributed to 22 graduate students and analysis showed strong reliability with a

Cronbach's coefficient alpha of 0.90. The researcher changed some wording to ensure these items fit the context of this study. The phrase *instructor-led sessions* in item 2 and 5 was deleted. Item 3 was broken into three items. The same CVR process and six experts who responded to the interaction subscales also commented on the satisfaction subscale. Their ratings data are shown below (see Figure 3-2). Item 2 and 3 were removed from the satisfaction scale with CVR smaller than 0.99. Hence, there were five items in the final version of satisfaction scale (Appendix B). Based on the pilot data (n = 111), the Cronbach's coefficient alpha value for satisfaction scale was 0.93.

Although strong choices in terms of alignment to the purposes of this study, the subscales for the three forms of interaction and student satisfaction represented the weakest of measurement tools. They lacked a close examination of validity, and the reliability data were based on a population of graduate students alone. Based on the

No.	Items	CVR	Decision
1	Overall, I am satisfied with this class.	1.00	kept
2	The course was a useful learning experience to me.	0.67	removed
3	This course contributed to my personal development.	0.33	removed
4	This course contributed to my educational development.	1.00	kept
5	This course contributed to my professional development.	1.00	kept
6	I am satisfied with the level of interaction that happened in this course.	1.00	kept
7	In the future, I would be willing to take a fully online course again.	1.00	kept

Figure 3-2. CVR value of each item in the satisfaction scale.

CVR and pilot data reliability analysis, these subscales appeared to measure what they set out to measure in a consistent way. Table 1 offers a summary of the items, decisions made, and reliability analyses for each subscale.

Results of Pilot Study

Descriptives

Of 111 respondents, 22.5% of them were males, 77.5% females, 64.9% of the respondents were married, and 35.1% were single. As for age distribution, most respondents were between the ages of 18-25 (33.3%) and 26-35 (49.5%). About 13.5% of the respondents were aged between 36 and 45. Only 3.6% reported their age between 46 and 55. More than half of the respondents (62.2%) took undergraduate-level courses, 21.6% of them took graduate-level courses, and 16.2% (38.7%) spent about 6-10 hours online per week (see Table 2). A few respondents

Table 1

A Summary of Independent Variable Subscales

Subscales	Final number of items	Number of items removed	Number of items combined	Cronbach's alpha from the pilot study
Learner-learner interaction	8	0	4	0.99
Learner-instructor interaction	6	2	3	0.88
Learner-content interaction	3	3	0	0.92
Satisfaction	5	2	0	0.93

Table 2

Hours Spent Online Per Week

Hours	Number	Percentage
Less than 5 hours	30	27.0%
6-10 hours	43	38.7%
11-15 hours	22	19.8%
16-20 hours	8	7.2%
Above 20 hours	8	7.2%

spent 16-20 hours or more than 20 hours online per week.

Based on Table 3, the average score of each subscale was higher than the midpoint score of each corresponding subscale, except for the learner-learner interaction subscale, which had a mean score slightly lower than the median score of three.

Correlation Analysis

Correlation analysis of the pilot study was run with 108 respondents since there

Table 3

Average Score for Each Scale

Subscales	Range	Midpoint	*M*	*SD*
Learner-learner (8 items)	1-5	3	2.86	1.14
Learner-instructor (6 items)	1-5	3	3.85	0.93
Learner-content (3 items)	1-5	3	3.93	1.01
Internet self-efficacy (8 items)	1-7	4	5.33	1.31
Self-regulated learning (12 items)	1-7	4	4.04	0.81
Satisfaction (5 items)	1-5	3	4.02	0.98

were three people with missing values for subscales. Based on correlations among independent variables shown in Table 4, they did not show red flags for multicollinearity since these correlations were all smaller than 0.80.

Table 5 shows a summary of correlation and *r* square values of the pilot study compared to the *r* square values in previous research. Three types of interaction and Internet self-efficacy were significantly correlated with satisfaction. These relationships were all positive. However, self-regulated learning was negatively correlated with satisfaction, which was not significant. In comparison to the *r* square values in previous research, the *r* square values in the pilot study for learner-instructor interaction and learner-content interactions fell in the range of previous *r* square values. Internet self-efficacy has a much larger *r* square than that in former research.

Table 4

Correlations among Independent Variables and Student Satisfaction for Pilot Data

	Learner-learner	Learner-instructor	Learner-content	Internet self-efficacy	Self-regulated learning	Satisfaction
Learner-learner	—	.430**	.288**	.057	.004	.246*
Learner-instructor		—	.499**	.220*	.115	.542**
Learner-content			—	.263**	.050	.664**
Internet self-efficacy				—	.063	.437**
Self-regulated learning					—	-0.004
Satisfaction						—

**p* < .05. ***p* < .01

Table 5

Correlations and R *Square Values Between Predictors and Satisfaction Compared to the Values in Previous Studies*

Subscales	Satisfaction (*r*)	Satisfaction (*r* square)	Satisfaction (*r* square: based on previous research)
Learner-learner interaction	0.246*	0.06	0.15 ~ 0.49
Learner-instructor interaction	0.542**	0.29	0.08 ~ 0.65
Learner-content interaction	0.664**	0.44	0.00 ~ 0.40
Internet self-efficacy	0.437**	0.19	0.01
Self-regulated learning	-0.004	0.00	F(2, 636) = 5.00**

Note. There was no information for the *r* square value of self-regulated learning. Hence, *F* value was provided in this table.
$^*p < .05$. $^{**}p < .01$.

Learner-learner interaction had a lower *r* square compared to the minimum in previous research. The *r* square value for self-regulated learning in former research was almost zero, which differed from the result of pilot study where the effect of self-regulated learning on satisfaction was significant.

Data Analysis

Where relevant, analyses regarding statistical significance testing used an alpha level of 0.05. The data was analyzed with SPSS 16.0 and HLM 6.0 for Windows. Two chi-squares were performed to identify representativeness of the sample. The first compared the number of courses from each program with the number of course offerings. The second analysis compared the number of student survey responses from each program with the number of enrolled students.

A brief summary of basic student demographics (gender, marital status, age, course level, and hours spent online per week) and for each item and subscale is presented first. To determine the internal consistency of items in each scale, a Cronbach's alpha reliability test was conducted. To determine the extent to which each independent variable correlated with student satisfaction, bivariate correlation analyses was performed to understand the relationships among three types of interactions, Internet self-efficacy, self-regulation, and student satisfaction. Pearson product moment correlation analysis was chosen since interaction, Internet self-efficacy, self-regulation, and satisfaction were all continuous variables. In addition, performing Pearson correlation analysis was a necessary step before testing a causal relationship between independent and dependent variables. The Pearson correlation coefficients (r), ranging between -1 and +1, indicated the strength and the direction of each independent variable with student satisfaction.

As a preliminary step towards HLM, a multiple regression analysis was performed by entering all predictors simultaneously to test for violations of methodological assumptions in the data. Specifically, the tests involved detecting multivariate outliers and determining to what degree individual outliers may bias the results. Further, since the predictors were likely correlated, a test for multicollinearity was performed first through bivariate correlation and then through multiple regression. Correlation values with r larger than 0.80 indicated possible multicollinearity. Based on the values of NIF and tolerance values in multiple regression, the problems of multicollinearity were indicated.

HLM was performed to address the research questions regarding the extent to which the combined and individual independent variables predicted student satisfaction, the unique variance each predictor explained, and the direct and moderating effects of class-level predictors on student satisfaction. HLM is a statistical technique which takes into account the influence of clustering to better predict the dependent variable. HLM was chosen since the data collected involved nesting with two levels. Student level (level-1) data was nested within the specific classes (level-2) students attend. Student variables, which were continuous data, included the scores for predictors and student satisfaction. Class-level variables were categorical including course category (undergraduate, undergraduate/graduate, or graduate) and the programs offering the course (Instructional Technology & Learning Sciences; Communicative Disorders and Deaf Education; Family, Consumer, and Human Development; Psychology; Special Education and Rehabilitation; School of Teacher Education & Leadership; and Health, Physical Education, and Recreation). Both course category and program were categorical variables so they were dummy coded before HLM was performed.

Equations 1 and 2 represent a two-level hierarchical linear model. Equation 1 presents the level-1 regression equation (student level) in which Y denotes student satisfaction, X_1 learner-leaner interaction, X_2 learner-instructor interaction, X_3 learner-content interaction, X_4 Internet self-efficacy, and X_5 self-regulated learning.

Equation 2 (class level) represents intercept β_0, and five slopes for predictors β_1 through β_5. W_1 represents course category, and W_2 the program. e_{ij} is the student-level residual variance. μ_{0j} through μ_{5j} refer to class-level variance components.

Level 1: $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + e_{ij}$ (1)

Level 2: $\beta_0 = \gamma_{00} + \gamma_{01} W_{1j} + \gamma_{02} W_{2j} + \mu_{0j}$ (2)

$$\beta_1 = \gamma_{10} + \mu_{1j}$$

$$\beta_2 = \gamma_{20} + \mu_{2j}$$

$$\beta_3 = \gamma_{30} + \mu_{3j}$$

$$\beta_4 = \gamma_{40} + \mu_{4j}$$

$$\beta_5 = \gamma_{50} + \mu_{5j}$$

For HLM analysis, a null model was performed without any student-level and class-level predictors in order to know the extent to which course difference (clustering effect) explains variations in student satisfaction.

To answer research questions two through five regarding the significant predictor, the uniqueness of significant predictors, and the extent to which the combination of predictors explains in student satisfaction, five variables (three types of interaction, Internet self-efficacy, and self-regulated learning) were entered as student-level predictors in an HLM analysis, without the inclusion of class-level predictors.

To answer the question regarding the direct effect of class-level predictors on student satisfaction, two class-level variables were entered as predictors of the intercept. As for the question regarding the moderator effect of class-level variables on student satisfaction, two class-level variables were entered into the significant slopes.

Table 6 shows an overview of the analyses performed in this study with the purpose description for each of them.

Table 6

An Overview of the Analyses Performed in the Study

Analysis	Purpose	Page number
Representativeness analysis	Supporting analysis	54
Reliability of the measures	Supporting analysis	56
Regression diagnosis	Preliminary analysis for HLM	57
Correlation analyses	Answer research question 1; preliminary analysis for HLM	60
HLM analyses with student-level predictor	Answer research questions 2, 3, & 4	61
HLM analyses with the inclusion of class-level predictors	Answer research question 5	68

CHAPTER IV

DATA ANALYSIS

Data Deleted

There were 221 survey responses from students who took online courses in the fall semester of 2009. Forty-one survey responses were deleted for one of the following reasons. Four were the sole respondents from their respective course, voiding the ability to include them in the HLM and six students responded to more than one course title (one of their responses was randomly selected to maintain independence of the data). All 19 responses from PSY 3210 were removed because the survey link was distributed to both face-to-face and distance members of a class taught to a dual population. Seven responses came from courses outside the college of education. Five students did not complete the survey. In all, 180 responses were maintained in the sample for the full study.

Descriptive Analyses: Demographics

Table 7 revealed the demographics distributions for gender, marital status, and age. There were more female respondents than male respondents, which is similar to the findings of other studies in distance learning environments where female respondents were the majority (60% to 89%) of online survey respondents (Chejlyk, 2006; Rodriguez Robles, 2006). Most of the respondents were married. Most respondents were either 18-25 or 26-35 years old. Only a few were 36 and older, which corresponds to Rodriguez Robles (2006) where 76% of the respondents aged

Table 7

Respondent Distributions for Gender, Marital Status, and Age

	Frequency	Percent
Gender		
Male	48	27%
Female	132	73%
Marital status		
Married	136	76%
Single	44	24%
Age		
18-25	74	41%
26-35	62	34%
36-45	28	16%
46-55	16	9%
Above 56	0	0%

from 21 to 40 years old, and Chejlyk (2006) where 56% of respondents aged between 18 and 35 years old.

According to Table 8, the courses were categorized into three levels: undergraduate level (1000-4000-level courses), undergraduate/graduate level (5000-level courses), and graduate level (6000-level courses). More than half of the respondents (80%) were taking undergraduate-level courses. Eleven percent of them were from graduate-level courses. Only 9% of the respondents were from undergraduate/graduate-level courses.

Most students spent less than 5 hours or 6-10 hours online for the class each week. Generally, not many respondents spent more than 10 hours online or on

Table 8

Course Level and Hours Spent Online Per Week

	Frequency	Percent
Course level		
Undergraduate level	144 (20 courses)	80%
Undergraduate/graduate level	17 (4 courses)	9%
Graduate level	19 (2 courses)	11%
Hours spent online per week		
Less than 5 hours	85	47%
6-10 hours	65	36%
11-15 hours	11	6%
16-20 hours	10	6%
Above 20 hours	9	5%

Blackboard (see Table 8).

Representativeness of the Sample

Chi-square analyses were performed first to compare the number of courses from each program with the number of course offerings, and then to compare the number of student survey responses from each program with the number of enrolled students in each program.

An assumption of chi-square is that at least five cases are present for any expected values. Programs with fewer than five responses were collapsed into another category. Before performing chi-square, Special Education and Rehabilitation and the School of Teacher Education and Leadership were combined into one category in order to meet this assumption. The nonsignificant result $\chi^2(5) = 5.84$, $p = .32$ in Table

9 indicates that the responding courses did not systematically differ from the offered courses at a statistically significant level. The response rate from the Instructional Technology and Learning Sciences program is higher than those from other programs, which may imply that the data is more representative of the students from Instructional Technology and Learning Sciences than education as a whole.

When the unit of analysis was changed to students, systematic differences were found with $\chi^2(6) = 128.23$, $p < .001$ (see Table 10). Some programs had only single courses (Special Education and Rehabilitation; School of Teacher Education and Leadership; and Health, Physical Education, and Recreation) participating. For instance, there were 172 enrolled in five courses offered through the program of

Table 9

Offered Courses Compared to Responding Courses

Program	Number of courses offered	Number of courses with student responses	% (responding courses against offered course)
Instructional Technology & Learning Sciences	5	4	80%
Communicative Disorders and Deaf Education	23	3	13%
Family, Consumer, and Human Development	20	9	45%
Psychology	29	7	24%
Combined: Special Education and Rehabilitation and School of Teacher Education & Leadership	5	2	40%
Health, Physical Education, and Recreation	5	1	20%
Total	87	26	29.89%

Table 10

Enrolled Students Compared with the Number of Responses

Program	Number of enrolled students	Number of student survey responses	% (number of responses against that of enrolled students)
Instructional Technology & Learning Sciences	103	29	28%
Communicative Disorders and Deaf Education	991	14	1%
Family, Consumer, and Human Development	717	84	12%
Psychology	588	42	7%
Special Education and Rehabilitation	60	6	10%
School of Teacher Education & Leadership	37	3	8%
Health, Physical Education, and Recreation	172	2	1%
Total	2668	180	7%

Health, Physical Education, and Recreation. However, only one class out of these five classes was approachable and it only had two student responses. Those with either small enrollments (INST 5120/6120, COMD 2910, FCHD 4220, PSY 2950, PSY 3460), or enrollments accounting for a small portion of the program's total course offerings (FCHD 1010, FCHD 2100, FCHD 3100, HEP 3000) may account for some of these statistically significant differences.

Descriptives of the Measures (Scales) and Reliability

Table 11 indicated the average score and reliability information for each scale based on the sample collected during fall semester 2009. Similar to the pilot study, each subscale had an average score higher than the midpoint of their corresponding scale except for the learner-learner interaction scale which had a mean slightly lower

Table 11

Average Score and Reliability Information for Each Scale

Subscales	Number of items	Range	Midpoint	*M*	*SD*	*α*
Learner-learner	8	1-5	3	2.90	1.22	0.94
Learner-instructor	6	1-5	3	3.66	0.94	0.83
Learner-content	3	1-5	3	4.08	0.99	0.92
Internet self-efficacy	8	1-7	4	5.32	1.17	0.92
Self-regulated learning	12	1-7	4	4.35	1.01	0.82
Satisfaction	5	1-5	3	4.24	0.79	0.87

Note. α refers to Cronbach's alpha.

than the midpoint score 3. The Cronbach's coefficient alpha values for six subscales were all larger than 0.80, presenting good reliability for each scale.

Regression Diagnosis

The regression diagnosis was performed in terms of regression assumptions, outliers, and multicollinearity, to make sure the dataset was ready for any further regression analyses.

Assumptions of Multiple Regression

Linearity, independence of residuals, and homoscedasticity are important assumptions to multiple regression. These assumptions need to be met before performing multiple regression. If any violations of assumptions are detected, multiple regression analysis cannot be used. Appendix H shows the distribution of the dependent variable. Although the distribution is skewed (Skewness: -1.352; Kurtosis:

2.158), there were no outliers. With the lack of outliers, a decision was made to keep data in their raw form rather than do a nonlinear transformation (Knobloch, Miller, Bond, & Mannone, 2007).

The assumption of linearity was tested by looking at the partial bivariate scatterplots between each independent variable and the dependent variable. The plots in Appendix H showed varied degrees of linear relationship between each predictor and the dependent variable. Nonlinear relationships were not found which met the assumption of linearity. Furthermore, the scatterplot of the predicted value against residuals (Appendix H) revealed no relationship, which also indicates the linearity assumption was not violated. All in all, the linearity assumption was clearly met.

Independence of residuals was examined by the histogram of the frequency of standardized residuals (Appendix H). The normal distribution of the standardized residuals in the plot indicates no violations of the normality of residuals.

The scatterplots of independent variables against residuals (Appendix H) were examined to determine if the assumption of homoscedasticity was violated. Based on the five plots, the dots were equally distributed around the horizontal line of zero except for some outliers which did not take a major influence, which indicated constant variance across a range of independent variables. Hence, the assumption of homoscedasticity was fulfilled.

Outliers

Outlier detection is important because it helps researchers avoid reporting misleading results. Outliers are data points which do not fit the rest of the data. The analysis result from the contaminated data with outliers will be biased from the accurate report without outliers existing. Leverage and Cook's Distance were two approaches used to determine outliers.

In terms of Cook's Distance statistics, there were no outliers showing with the maximum value of 0.498 (Table 12), which is smaller than the required value of 1. The maximum of Centered Leverage Value was larger than three times of the mean, which revealed outliers in the data. By checking the data, four cases were found as outliers in terms of leverage statistics. Based on the visual method, the histogram of Centered Leverage Value (Appendix H) was a little skewed and showed an extension of a softly sloping curve on the right side of the distribution, which did not appear to have extreme outliers. Hence, no cases were excluded in terms of leverage and influence statistics.

Multicollinearity

Multicollinearity refers to high correlations among a set of independent variables. When highly correlated independent variables are included in the same regression equation model, multicollinearity occurs and leads to unstable regression coefficients

Table 12

Residual Scores for Satisfaction

	Minimum	Maximum	*M*	*SD*	*N*
Centered Leverage Value	0.004	0.124	0.028	0.020	180
Cook's Distance	0.000	0.498	0.011	0.049	180

Note. Dependent variable is satisfaction.

which are not interpretable, as well as large standard errors. The redundant predictors involving multicollinearity need to be removed before any regressions equations can be interpreted.

To diagnose multicollinearity, bivariate correlations among predictors were examined. When two predictors completely overlap or almost overlap with each other, multicollinearity happens. That is, two predictors share too much variance and decrease their unique contribution to the prediction of the outcome. Any pairs of predictors with a squared correlation larger than 0.80 are likely to cause problems. The squared correlations for each pair of independent variables in Table 13 were smaller than 0.80, which indicated there might be no potential multicollinearity problems.

Table 13

Correlations among Independent Variables and Student Satisfaction

	Learner-learner	Learner-instructor	Learner-content	Internet self-efficacy	Self-regulated learning	Satisfaction
Learner-learner	—	.494**	.154*	.035	.157*	.177*
Learner-instructor		—	.442**	.222**	.171*	.392**
Learner-content			—	.226**	.428**	.684**
Internet self-efficacy				—	.183*	.181*
Self-regulated learning					—	.340**
Satisfaction						—

*$p < .05$. **$p < .01$.

The Variance Inflation Factor (VIF) and Tolerance values were examined to detect the problems of multicollinearity. According to Cohen, Cohen, West, and Aiken (2003), the rule of thumb is that when VIF values are higher than 10, and the Tolerance value is lower than 0.10, there might be serious problems with multicollinearity. VIF and Tolerance values for each predictor were examined and found to be in range. With no evidence of multicollinearity, HLM analysis was deemed appropriate in this case.

Correlation Analyses

In addition to providing needed information for assessing multicollinearity, the correlations between each predictor and student satisfaction from Table 13 also address research question one. All five predictors were significantly correlated with student satisfaction. The positive relationship of each predictor with satisfaction implied a tendency towards a higher satisfaction score when the scores of each independent variable increased. Learner-content interaction showed the strongest relationship with student satisfaction ($r = .684$, $p < .01$) while learner-learner interaction ($r = .177$, $p < .05$) and Internet self-efficacy ($r = .181$, $p < .05$) showed a very weak correlation with satisfaction. Learner-content interaction explained about 47% of the variance in student satisfaction, which is quite substantial.
Learner-instructor interaction and self-regulated learning explained 15% and 11% of the variance in student satisfaction respectively. Both learner-learner interaction and Internet self-efficacy contributed almost nothing to student satisfaction, with an unsubstantial *r* square value 0.03.

Hierarchical Linear Modeling (HLM) Analyses

with Student-Level Predictors

Null Model

A null model is the first step of building a multilevel model. Fully unconditional, a null model provides information about between-group variance and within-group variance in terms of the intra-correlation coefficient (ICC). In this null model, the ICC was 0.024, which indicated that 2.4% of the total variance in student satisfaction was accounted by the between-group variance. That is, the classes students attended explained only 2.4% of the variance in student satisfaction. It means that classes do not differ too much in the mean of student satisfaction.

Although an ICC value of 0.024 is not quite substantial, due to the independence of observations which violates the multiple regression assumptions, it is justified to continue performing a multilevel model analysis.

The Model with Five Level-1 Predictors

To address research questions two, three, and four, an expanded model beyond the null model is necessary. This expanded model includes five level-1 predictors (student level): three types of interaction, Internet self-efficacy, and self-regulated learning. These five predictor variables were entered into the level-1 equation, as illustrated in Equation 3. Equation 4 depicts the random intercept and random slopes without the inclusion of any level-2 predictors (class level).

Level 1: $Y = \beta_0 + \beta_1$(learner-learner interaction) + β_2(learner-instructor (3) interaction) + β_3(learner-content interaction) + β_4(Internet self-efficacy) + β_5(self-regulated learning) + e_{ij}

Level 2: $\beta_0 = \gamma_{00} + \mu_{0j}$ (4)

$\beta_1 = \gamma_{10} + \mu_{1j}$

$\beta_2 = \gamma_{20} + \mu_{2j}$

$\beta_3 = \gamma_{30} + \mu_{3j}$

$\beta_4 = \gamma_{40} + \mu_{4j}$

$\beta_5 = \gamma_{50} + \mu_{5j}$

When five level-1 predictors were added beyond the null model, the results showed that three parameters (Table 14) were significant in the model: intercept (γ_{00}), learner-instructor interaction (γ_{20}), and learner-content interaction (γ_{30}). γ_{00} referred to the mean score of student satisfaction when the score of each of the other four predictors was the average. γ_{20} reflected the average slope for leaner-instructor

Table 14

Coefficient Estimates of the Model with Five Level-1 Predictors

	Parameter	Estimate	*SE*	*df*	*t*-ratio
Intercept	β_0 (γ_{00})	4.214	0.048	25	88.420***
Learner-learner interaction	β_1 (γ_{10})	-0.021	0.040	25	-0.511
Learner-instructor interaction	β_2 (γ_{20})	0.122	0.055	25	2.237*
Learner-content interaction	β_3 (γ_{30})	0.604	0.069	25	8.762***
Internet self-efficacy	β_4 (γ_{40})	-0.003	0.043	25	-0.063
Self-regulated learning	β_5 (γ_{50})	-0.025	0.071	25	-0.348

*$p < .05$. ***$p < .001$.

interaction across the various courses. γ_{30} referred to the average slope for leaner-content interaction across the courses. All five slopes are assumed to be random.

Both learner-instructor interaction ($\beta_2 = 0.122$, $t = 2.237$, $p < .05$) and learner-content interaction ($\beta_3 = 0.604$, $t = 8.762$, $p < .001$) significantly contribute to student satisfaction when accounting for class effects, which addressed the third research question regarding which variable remained significant when all predictors were used to predict student satisfaction. The directions of coefficients for both learner-instructor interaction and learner-content interaction were positive, implying students having more interaction with their instructor were more likely to have higher satisfaction compared to their counterparts with lower learner-learner interaction. Similarly, students who had higher scores on learner-content interaction were more satisfied with the online course they were taking.

Table 15 reveals that the variance components are only significant for Internet self-efficacy and self-regulated learning, which indicates that the variances in the slopes of Internet self-efficacy and self-regulated learning are accounted for by class differences. In other words, class differences take effect on the level-1 slopes for Internet self-efficacy and self-regulated learning, which in turn support the decision of employing multilevel model analysis, regardless of the small ICC. However, on the other hand, Internet self-efficacy and self-regulated learning are not the focus because both of them are not significant predictors for student satisfaction (see Table 14). The focus is supposed to be learner-instructor interaction and learner-content interaction,

Table 15

Variance Components of the Model with Five Level-1 Predictors

Random effect	Variance component	*df*	Chi-square	*p*-value
Intercept (U_0)	0.118	10	9.603	>0.500
Learner-learner interaction (U_1)	0.068	10	8.487	>0.500
Learner-instructor interaction (U_2)	0.077	10	12.404	0.258
Learner-content interaction (U_3)	0.191	10	13.749	0.184
Internet self-efficacy (U_4)	0.110	10	18.500	0.047
Self-regulated learning (U_5)	0.245	10	30.976	0.001

both of which are significant predictors for student satisfaction. However, both of their variance components are not significant, which implies that class difference does not have an impact on the slopes for learner-instructor interaction and learner-content interaction. The nonsignificance of variance might happen when the degree of freedom is small even though there are actual cluster effects.

According to Table 15, the degrees of freedom of 10 are so small and they might lead to the nonsignificant results for the variance components of learner-instructor interaction and learner-content interaction.

R^2 for Level-1

Slightly different from the R^2 in regular OLS regression, the R^2 in multilevel models is interpreted as the proportion of reduction in predictor error. This study is a two-level model; hence, the proportions of reduction for level-1 and level-2 are supposed to be calculated separately. However, since there are no level-2 predictors in the model with five level-1 predictors, it is meaningless to calculate the R^2 for level-2 at this point. The R^2 in multilevel models is calculated through the comparison of two models, which are the null model and the model with five predictors (see Table 16). The R^2 for level-1 is 0.494. By including the five level-1 predictors, the predictive ability of the final model compared to the model with five level-1 predictors is improved approximately by 50%, which answered the second research question with regard to the overall contribution of the combination of predictors.

Uniqueness of the Significant Predictor

Learner-instructor interaction and learner-content interaction are two predictors which showed significance out of five predictors. Hence, the uniqueness is calculated for learner-instructor interaction and learner-content interaction, which answered the fourth research question in relation to the unique contribution of the significant predictor.

The uniqueness for learner-instructor interaction approaches zero since the residual of the model encompassing four predictors without learner-instructor interaction included remains almost the same as the residual of the model with five level-1 predictors.

As for the uniqueness of learner-content interaction, compared to the model

Table 16

Comparisons of the Models with Fixed Effects

Model	σ_e^2	σ_{u0}^2
Null model	0.6032	0.0146
The model with five level-1 predictors	0.2923	0.0205

with four level-1 predictors (with the exclusion of learner-content interaction), the level-1 residual of the model with five predictors is reduced from 0.455 to 0.215 (see Table 17), a 24% reduction. That is, learner-content interaction itself contributes an additional 24% of the variance beyond the model with four level-1 predictors (without learner-content interaction) where 45.5% of the variance is reduced compared to the null model.

One way to assess uniqueness is to calculate it based on the overall variance of the predictors as shown above. Another approach is calculating the reduction of left-over variance not explained by the predictors. The reduction is calculated only for learner-content interaction but not for learner-instructor interaction since the residual variance remained almost the same after learner-instructor interaction is entered as a fifth predictor.

Compared to the model with four level-1 predictors, the level-1 residual of the

Table 17

Uniqueness of Learner-Instructor Interaction and Learner-Content Interaction

	R^2	Uniqueness
The model with five level-1 predictors against the null model	0.455	—
The model with four level-1 predictors (without learner-content interaction) against the null model	0.215	0.240 (24%)
The model with four level-1 predictors (without learner-instructor interaction) against the null model	0.453	0.002 (0.2%)

model with five level-1 predictors is reduced from 0.342 to 0.138 (see Table 18), a 40.35% of the reduction based on the left-over residual variance. That is, the residual of student satisfaction is reduced by around 40% by adding learner-content interaction as a level-1 predictor, compared the model of five level-1 predictors with the model of four level-1 predictors where learner-content interaction is excluded.

Hierarchical Linear Modeling (HLM) Analyses with the Inclusion of Class-Level Predictors

To answer research question five, class-level predictors need to be entered into the model. Before performing HLM analyses with two level-2 predictors (class level), the number of units for each category in two level-2 predictors were recategorized in order to make predictors meaningful, as well as to reduce the number of the dummy-coded variables for each predictor.

Table 18

Reduction of Error Variance in Predicting Student Satisfaction When Entering Learner-Content Interaction as Fifth Predictor (Effect on Level-1 Variance Component)

	σ_e^2	% of reduction
The model with four level-1 predictors (without learner-content interaction)	0.342	
The model with five level-1 predictors	0.204	
$\Delta\sigma_e^2$ between two models	0.138	40.35%

Predictor: Course Category

The courses were originally categorized three ways: undergraduate, undergraduate/graduate, and graduate. There are only four courses in the undergraduate/graduate level and two courses in the graduate level. Given the sparse number of graduate level courses it does not make sense to have three categories for course category predictor. Hence, these four courses were moved either to the graduate-level category or to the undergraduate-level category.

A detailed examining of the four combined graduate/undergraduate course rosters was used to make a meaningful reassignment. Students in INST 5120/6120 were all from masters programs. Hence, INST 5120/6120 was moved to the category of graduate-level courses. Similarly, since INST 5140/6140 had 19 graduate students and 2 undergraduate students, it was categorized as graduate. PSY 5330 included all students from undergraduate programs and was moved to undergraduate level. COMD 5070 was categorized to the undergraduate-level courses since two out of three responding students were undergraduates. Table 19 shows the distribution of courses in terms of two course categories: undergraduate level and graduate level.

Table 19

Course Category for HLM

	Frequency	Percent
Undergraduate level	154 (22 courses)	86
Graduate level	26 (4 courses)	14

Predictor: Program

There are seven programs in the College of Education. Special Education and Rehabilitation; School of Teacher Education and Leadership; and Health, Physical Education, and Recreation each had a single class participate in the survey. Since each level-2 predictor needs at least two cases, a decision to collapse categories was made. Based on the nature of course content, Instructional Technology and Learning Sciences, Special Education and Rehabilitation, and School of Teacher Education and Leadership were combined under the same category. Similarly, Health, Physical Education, and Recreation was combined with Psychology. Table 20 shows the final four categories for the program predictor.

Main Effects of Class-Level Predictors on Student Satisfaction

Two level-2 (class level) predictors, course category and program, were entered and examined simultaneously in the model with five level-1 predictors.

Table 20

Categories of the Programs for HLM

Program	Number of courses with student responses
Category 1: Combined: Instructional Technology & Learning Sciences, Special Education and Rehabilitation, and School of Teacher Education & Leadership	6
Category 2: Communicative Disorders and Deaf Education	3
Category 3: Family, Consumer, and Human Development	9
Category 4: Combined: Psychology and Health, Physical Education, and Recreation	8

Course category and three program dummy codes were entered as predictors of the intercept. Course category, which was the class-level predictor, included the undergraduate-level and graduate-level courses.

The program was transformed into three dummy codes in terms of the simple coding technique by which the group that was the combination of three programs (category 1: Instructional Technology and Learning Sciences, Special Education and Rehabilitation, and School of Teacher Education and Leadership) was treated as a reference group. This was used to compare with the other three groups separately (category 2, category 3, and category 4). Courses from Instructional Technology and Learning Sciences were the majority in category 1. Category 1 was chosen as the reference group since the researcher was in the program of Instructional Technology and Learning Sciences and was interested in comparing the Instructional Technology and Learning Sciences program with the rest of the programs in the other three categories.

Table 21 reveals that neither course category nor programs were significant, indicating that none of the class-level predictors were helpful in predicting student satisfaction. In other words, there were no direct effects of class-level predictors on student satisfaction.

Moderator Effects of Class-Level Predictors

The moderator effects referred to the cross-level interactions between student-level predictors and class-level predictors. In the model with five level-1 predictors, learner-instructor interaction and learner-content interaction are two

Table 21

Coefficient Estimates in the Model of Five Level-1 Predictors with Two Class-Level Predictors Entered into the Intercept

	Parameter	Estimate	*SE*	*df*	*t*-ratio
Intercept	β_0 (γ_{00})	4.210	0.104	21	40.628***
Course category	(γ_{01})	-0.028	0.221	21	-0.127
Program dummy 1	(γ_{02})	0.080	0.251	21	0.317
Program dummy 2	(γ_{03})	-0.009	0.211	21	-0.042
Program dummy 3	(γ_{04})	0.091	0.223	21	0.408
Learner-learner interaction	β_1 (γ_{10})	-0.015	0.043	25	-0.346
Learner-instructor interaction	β_2 (γ_{20})	0.130	0.057	25	2.280*
Learner-content interaction	β_3 (γ_{30})	0.607	0.066	25	9.155***
Internet self-efficacy	β_4 (γ_{40})	-0.005	0.044	25	-0.108
Self-regulated learning	β_5 (γ_{50})	-0.036	0.075	25	-0.483

*$p < .05$. ***$p < .001$.

significant predictors (see Table 14). Hence, the moderator effects of two class-level predictors were only tested for the slopes of these two level-1 predictors. Therefore, two class-level predictors were entered into the intercept and two student-level predictors which were learner-instructor interaction and learner-content interaction. The moderator effects of the class-level predictors on the impact of learner-learner interaction, Internet self-efficacy, and self-regulated learning on students satisfaction were not discussed.

However, the variances for both learner-instructor interaction and learner-content interaction were not significant (see Table 15), which would happen when only a small amount of the groups were counted by the HLM program.

Depending on the number of predictors in this study, the HLM program would only include classes where the number of students is at least larger than the number of predictors. That is, not all of the 26 courses were taken into account by the HLM program, which led a reduction in degrees of freedom. Given the small degrees of freedom, it is easy to have nonsignificant variance components statistically; however, in the real situation, class difference may still have an impact on the slopes of learner-instructor interaction and learner-content interaction on student satisfaction.

Tables 22 and 23 are proofs for the varying slopes of learner-instructor interaction and learner-content interaction on student satisfaction, which were a demonstration of the substantial effect of class difference on the slope of learner-instructor interaction and learner-content interaction based on courses with at least six students.

The *r* squares for both learner-instructor interaction (.066 ~ .966) and learner-content interaction (.203 ~ .982) vary to a large degree, from contributing almost none to the variance of student satisfaction to almost all of the variance in student satisfaction. Like correlation coefficients, regression coefficients are on a scale from -1 to 1. The regression coefficients of learner-instructor interaction on student satisfaction ranged from -0.053 to 0.671. The regression coefficients of learner-content interaction on student satisfaction ranged from 0.123 to 0.876. Both of their regression coefficient values show a large variation between 0 to 1. While this implies variations in slope all of the relationships are either nonexistent or positive. Several regression coefficients of learner-instructor interaction and learner-content

Table 22

Bivariate Correlations and Regression Coefficients of Learner-Instructor Interaction on Student Satisfaction

Course number	Bivariate correlation	*r* square	Regression coefficients	Tolerance	VIF
2	0.257	0.066	0.671	0.235	4.263
3	0.588	0.346	0.078	0.362	2.764
4	0.880	0.774	—	0.005	199.381
6	0.250	0.063	—	0.076	13.189
8	0.334	0.112	0.066	0.799	1.251
10	0.481	0.231	—	0.096	10.457
12	0.359	0.129	0.103	0.787	1.271
14	0.584	0.341	—	0.139	7.202
17	0.664	0.441	—	0.000	5028.3
18	0.131	0.017	-0.053	0.596	1.677
24	0.983	0.966	—	0.019	52.319

—: The regression coefficients that can not be interpreted due to multicollinearity.
The regression was performed with five predictors.

interaction could not be interpreted due to multicollinearity problems where a tolerance smaller than 0.20 and a VIF larger than 10 were shown.

The varying bivariate correlations and regression coefficients of learner-content interactions proved that student satisfaction differed depending on the class. In other words, the difference of class did have an impact on the effect of learner-instructor interaction and learner-content interaction on student satisfaction. The variance components of Internet self-efficacy and self-regulated learning were significant (see Table 15). Despite the significant variance components, both predictors have

Table 23

Bivariate Correlations and Regression Coefficients of Learner-Content Interaction on Student Satisfaction

Course number	Bivariate correlation	*r* square	Regression coefficients	Tolerance	VIF
2	0.844	0.712	0.876	0.644	1.552
3	0.945	0.893	—	0.160	6.263
4	0.907	0.823	—	0.008	130.395
6	0.587	0.345	—	0.204	4.899
8	0.849	0.721	0.776	0.563	1.776
10	0.613	0.376	—	0.087	11.541
12	0.772	0.596	0.551	0.539	1.854
14	0.451	0.203	0.123	0.394	2.536
17	0.956	0.914	—	0.093	10.753
18	0.601	0.361	0.617	0.597	1.676
24	0.991	0.982	—	0.018	54.881

—: The regression coefficients that can not be interpreted due to multicollinearity.
The regression was performed with five predictors.

nonsignificant regression coefficients.

Separate Tests for Two Class-Level Predictors

Two level-2 (class level) predictors, course category and program, were examined separately in two models instead of entering both of them simultaneously in a model. First, course category—including undergraduate-level and graduate level courses—was added as a predictor for the intercept and two significant level-1 slopes, which were learner-instructor interaction and learner-content interaction. The model entered with course category as level-2 predictor only showed significance ($p < .05$)

for the slope of learner-content interaction, which indicated that the level-2 predictor, course category, took effect on the influences of learner-content interaction on student satisfaction. Hence, course category was maintained for learner-content interaction in the combined model.

Secondly, the program that was regrouped into four categories was then entered into the model as level-2 predictors for the intercept and each of the significant level-1 slopes, which were learner-instructor interaction and learner-content interaction. The result showed that program dummy codes only had influence on the slope of learner-content interaction on student satisfaction. Hence, the program dummy codes were only kept as level-2 predictors for the slope of learner-content interaction in the combined model, and were removed from the other four level-1 slopes which were learner-learner interaction, learner-instructor interaction, Internet self-efficacy, and self-regulated learning.

The Combined Model with Two Class-Level Predictors

As indicated in the previous step, two separate tests for two class-level predictors were conducted. Two class-level predictors—course category and program—were only significant for the slope of learner-content interaction. Hence, these two class-level predictors were entered to the intercept as well as the slope of learner-content interaction. The result indicated that program was significant in predicting the slope of learner-content interaction while course category was not. Therefore, program was the only class-level predictor that was maintained in the final model.

The Final Model with One Class-Level Predictor

Level-2 predictors—course category and program—were entered only for the intercept and the slope of learner-content interaction on student satisfaction. However, the result showed that course category did not take any effect on either the intercept or the slope of learner-content interaction; hence, course category was removed from the final model. That is, program was the only level-2 predictor included in the final model.

The final model was represented in Equations 3 and 4. Interactions among five level-1 predictors were examined as well. None of them was significant; hence, the final model did not include any interaction terms of level-1 predictors.

Equation 5 represents the level-1 (student level) equation with five predictors. Equation 6 represents the random intercept and random slopes. Three program dummy codes were entered as level-2 predictors of the slope of learner-content interaction. Dummy code 1 represented category 2 (Communicative Disorders and Deaf Education) against category 1 (Instructional Technology & Learning Sciences), program dummy code 2 represented category 3 (Family, Consumer, and Human Development) against category 1, and program dummy code 3 represented category 4 (a combination of Psychology and Health, Physical Education, and Recreation) against category 1.

Level 1: $Y = \beta_0 + \beta_1(\text{learner-learner interaction}) + \beta_2(\text{learner-instructor interaction}) + \beta_3(\text{learner-content interaction}) + \beta_4(\text{Internet self-efficacy}) + \beta_5(\text{self-regulated learning}) + e_{ij}$ (5)

Level 2: $\beta_0 = \gamma_{00} + \gamma_{01}$(program dummy 1) + γ_{02}(program dummy 2) + (6)

γ_{03}(program dummy 3) + μ_{0j}

$\beta_1 = \gamma_{10} + \mu_{1j}$

$\beta_2 = \gamma_{20} + \mu_{2j}$

$\beta_3 = \gamma_{30} + \gamma_{31}$(program dummy 1) + γ_{32}(program dummy 2) +

γ_{33}(program dummy 3) + μ_{3j}

$\beta_4 = \gamma_{40} + \mu_{4j}$

$\beta_5 = \gamma_{50} + \mu_{5j}$

Deviance and the Akaike Information Criterion (AIC) are common techniques for the examination of model fit (Luke, 2004). Generally, deviance is used with nested models, and AIC with nonnested models. Lower deviance and AIC values refer to a better model fit. Compared to the null model and the model with five level-1 predictors (see Table 24), the final model had the lowest deviance and AIC. Compared to the null model, the final model is not a better fit ($\triangle\chi^2 = 12.14$, $df = 11$, $p > .05$). Similarly, there is no significant improvement comparing the model with five student-level predictors with the final model since the delta Chi square is not

Table 24

Respective Deviance and AIC for the Null Model and the Models with Random Effects

Model	Deviance	AIC
Null model	424.362	428.362
Model with five level-1 predictors	292.506	336.506
Final model	290.804	334.803

significant ($\triangle\chi^2$ = 0.28, df = 6, p > .05).

Table 25 reveals the results of HLM for the model with five level-1 predictors and the final model with five level-1 predictors and one level-2 predictor. In the model with five level-1 predictors, leaner-instructor interaction and learner-content interaction were two significant predictors. With the inclusion of three program dummy codes as level-2 predictors for learner-content interaction, learner-content interaction became the only one predictor which got significant, out of five level-1 predictors.

In terms of the variance components of level-2 random effects for the final model, it seemed that the class difference only took effect on self-regulated learning. The variance components of the intercept and the other four predictors were not significant, which might be possible since the degree of freedom (10) was so low. The variance might have a change to be significant given a larger degree of freedom. Learner-content interaction became the only significant predictor in the final model. This might be the result of adding additional predictors into the regression equation, which lowers the degrees of freedom for the analysis. γ_{00}, γ_{30}, γ_{32}, and γ_{33} were the four significant parameters in the final model. The intercept (γ_{00}) referred to an estimate of the average student satisfaction score when a student has an average score in learner-learner interaction, learner-instructor interaction, learner-content interaction, Internet self-efficacy, and self-regulated learning. γ_{30} indicated an average level-1 slope for learner-content interaction (β_3) across the classes. For each one unit increase in the score of learner-content interaction, the score of student satisfaction was

Table 25

Results of HLM

Level 1 predictors	Level 2 predictors	Final estimation of effects			Variance components of level-2 random effects				Comparison of variance components	
		Estimate	*SE*	*t*	$\sigma^2 u$	*df*	χ^2	*p* value	% of reduction	$\Delta\chi^2$
Model with five level-1 predictors										
Intercept (β_0)	(γ_{00})	4.214	0.048	88.420***	0.0138	10	9.603	>0.500		
LL interaction (β_1)	Intercept β_1 (γ_{10})	-0.021	0.040	-0.511	0.0047	10	8.487	>0.500		
LI interaction (β_2)	Intercept β_2 (γ_{20})	0.122	0.055	2.237*	0.0059	10	12.404	0.258		
LC interaction (β_3)	Intercept β_3 (γ_{30})	0.604	0.069	8.762***	0.0364	10	13.749	0.184		
ISE (β_4)	Intercept β_4 (γ_{40})	-0.003	0.043	-0.063	0.0122	10	18.500	0.047**		
SRL (β_5)	Intercept β_5 (γ_{50})	-0.025	0.071	-0.348	0.0598	10	30.976	0.001***		
Final model										
Intercept (β_0)	(γ_{00})	4.128	0.088	47.107***	0.01262	7	10.797	0.147		
	Program dummy 1 (γ_{01})	0.035	0.269	0.130						
	Program dummy 2 (γ_{02})	0.099	0.107	0.921						
	Program dummy 3 (γ_{03})	0.138	0.121	1.141						
LL interaction (β_1)	Intercept β_1 (γ_{10})	-0.001	0.040	-0.028	0.0031	10	8.690	>0.500		
LI interaction (β_2)	Intercept β_2 (γ_{20})	0.080	0.053	1.504	0.0021	10	11.328	0.332		
LC interaction (β_3)	Intercept β_3 (γ_{30})	0.987	0.112	8.774***	0.0011	7	7.839	0.347	96.29%	5.746*
	Program dummy 1 (γ_{31})	-0.204	0.372	-0.549						
	Program dummy 2 (γ_{32})	-0.499	0.121	-4.125***						
	Program dummy 3 (γ_{33})	-0.514	0.136	-3.790***						
ISE (β_4)	Intercept β_4 (γ_{40})	0.002	0.042	0.052	0.0113	10	18.135	0.052		
SRL (β_5)	Intercept β_5 (γ_{50})	-0.061	0.075	-0.810	0.0729	10	36.838	0.000***		

Note. LL interaction: learner-learner interaction, LI interaction: learner-instructor interaction, LC interaction: learner-content interaction, ISE: Internet self-efficacy, SRL: self-regulated learning. Program dummy code 1 represents category 2 (Communicative Disorders and Deaf Education) against category 1 (Instructional Technology & Learning Sciences). Program dummy code 2 represents category 3 (Family, Consumer, and Human Development) against category 1 Program dummy code 3 represents category 4 (a combination of Psychology program and the program of Health, Physical Education, and Recreation) against category 1.

increased by 0.987 units.

γ_{32} and γ_{33} were the two significant cross-level interactions. The coefficient of program dummy 2 (γ_{32}) was negatively significant, which referred to a tendency toward stronger positive slope of learner-content interaction on student satisfaction score in the program of Instructional Technology and Learning Sciences than in the program of Family, Consumer, and Human Development. Similarly, the coefficient of program dummy 3 (γ_{33}) was negatively significant, which indicated that students in the program of Instructional Technology and Learning Sciences were more likely to have a stronger influence on the positive slope of learner-content interaction than those in the combined Psychology and Health, Physical Education, and Recreation programs.

Moderator Effect of Program on the Relationship Between Learner-Content Interaction and Student Satisfaction

The variance component of β_3 (learner-content interaction) was reduced to 96.29% with the inclusion of three program dummy codes as the predictors of the slope of learner-content interaction (see Table 26), which was significant with $\Delta\chi^2$ = 5.746, $p < .05$. Even though 96.29 % of reduction was large, it might not be able to be generalized since only 11 courses were taken into account by the HLM. Furthermore, among those 11 courses incorporated into the HLM, the size of each varied to a certain degree. Variations in sample size might lead to a big sampling error to the size of reduction (96.29%). That is, the magnitude of the 96.29% of reduction might not be reliable, but the statistical significance level is reliable.

Table 26

Reduction of the Variance Component of the Slope of Learner-Content Interaction (σ_{u3}^2) when Program Was Entered as a Moderator

	σ_{u3}^2	χ^2	% of reduction
The final model without program as moderator of the slope of learner-content interaction	0.02858	13.586	
The final model	0.00106	7.839	
$\Delta\sigma_{u3}^2$ between two models	0.02752	5.746*	96.29%

CHAPTER V

DISCUSSION

This chapter provides a summary of findings in terms of the data analysis. The results of findings are discussed in light of the literature review. Finally, limitations and recommendations for future study are presented and discussed.

Summary

The study is a descriptive correlational study designed to investigate the relationship of student perceptions of learner-learner interaction, learner-instructor interaction, learner-content interaction, Internet self-efficacy, and self-regulated learning with student satisfaction in online learning environments. Furthermore, the extent to which the five independent variables could predict student satisfaction was examined. The direct and moderator effects of class-level predictors were explored as a final analysis

Findings and Discussions

Research Question One

Research question one is, to what extent does each predictor variable correlate with student satisfaction? The correlation analysis was used to answer the first research question regarding the degree to which each predictor correlated with student satisfaction. All five independent variables revealed a significantly positive correlation with student satisfaction, which indicated that the higher score on each of the independent variable, the higher student satisfaction. Out of five independent variables, learner-content interaction ($r = .684, p < .01$) had the highest correlation with student satisfaction, and learner-instructor interaction ($r = .392, p < .01$) followed.

Learner-learner interaction ($r = .177, p < .05$) correlated least with student satisfaction among three types of interaction. Consistent with previous studies, the direction of correlation between three types of interaction and student satisfaction was positive and also significant (Chejlyk, 2006; Rodriguez Robles, 2006; Sher, 2004). Internet self-efficacy ($r = .181, p < .05$) showed a very low correlation with student satisfaction, even though it was significant. As for self-regulated learning ($r = .340, p < .01$), it revealed a low correlation with student satisfaction as well. Compared to the pilot r^2 data in table 1, the r^2 (0.03) for learner-learner interaction was lower than any r^2 values in the range from 0.15 to 0.49. The r^2 of learner-instructor interaction (0.15) did fall within the rage of previously examined r^2 values (0.08 ~ 0.65), but was on the lower side of the range. The r^2 of learner-content interaction was a little higher than the r^2 range (0.00 ~ 0.40) in previous studies. The r^2 for Internet self-efficacy (0.03) was close to the r^2 value examined in previous research.

The r^2 values from the full study are similar to those of pilot study, except for Internet self-efficacy and self-regulated learning. The r^2 value of Internet self-efficacy is almost zero, lower than the value (0.19) from pilot study. The r^2 of self-regulated learning (0.11) is a little higher than the r^2 value (zero) in the pilot study. Reasons for the differences are unclear, note that some of the programs were not represented in the pilot phase, such as Teacher Education and Leadership, because no courses were offered. Beyond the courses offered, summer classes might also draw a slightly different demographic of student. No prior work reports r^2 values for self-regulated learning, and clearly more work is needed to determine the strength or lack of relationship with student satisfaction.

Research Question Two

Research question two is, to what extent does the combination of interaction, Internet self-efficacy, and self-regulated learning predict student satisfaction? In HLM, R^2 was used to interpret the total reduction of predictor error after all predictors were entered. That is, the proportional reduction of predictor error reflected the variance explained by the predictors which were entered beyond the null model. Based on the HLM analysis, R^2 was calculated separately for both level-1 (student level) and level-2 (class level).

A 49.4% reduction in variance was detected after five level-1 predictors were entered into the equation, which were three types of interaction, Internet self-efficacy, and self-regulated learning. In other words, these five level-1 predictors explained almost 50% of the variance in student satisfaction.

Research Question Three

Research question three is, which of the variables remain significant when all are used to predict student satisfaction? According to HLM analysis, among the five level-1 (student level) predictors, learner-instructor interaction and learner-content interaction were the two level-1 predictors that significantly predicted student satisfaction. Compared to learner-learner interaction and learner-instructor interaction, learner-content interaction was the strongest predictor of student satisfaction. The prominence of learner-content interaction was consistent with both Chejlyk (2006) and Keeler (2006). Other researchers found that either learner-learner or learner-instructor interaction was more predictive of student satisfaction (Battalio, 2007; Bolliger & Martindale, 2004; Jung et al., 2002; Rodriguez Robles, 2006).

Consistent with the findings from Puzziferro (2006) and Rodriguez Robles (2006), Internet self-efficacy was not a significant predictor for student satisfaction. Self-regulated learning in this study is not a significant predictor of student satisfaction, contrary to the study of Puzziferro (2006) where self-regulated learning significantly predicted student satisfaction. More research on the effect of self-regulated learning on student satisfaction is encouraged to verify the contrary results of this study and prior work.

Research Question Four

Research question four is, of those variables that combine for the best prediction of student satisfaction, how much unique variance in student satisfaction does the significant predictor explain? Based on HLM analysis, learner-content interaction and learner-instructor interaction were the only two independent variables which significantly contributed to student satisfaction in the model with five level-1 predictors. Twenty-four percent of the unique variance in student satisfaction was explained by learner-content interaction, compared to the model with four level-1 predictors: learner-learner interaction, learner-instructor interaction, Internet self-efficacy, and self-regulated learning. Learner-instructor interaction contributed almost nothing to the variance of student satisfaction beyond the model with four level-1 predictors where learner-instructor was not included.

Learner-content interaction as the largest unique contribution to student satisfaction makes sense, since learner-content interaction is the among the five level-1 predictors.

Research Question Five

Research question five is, do the class-level predictors (course category and program) affect student satisfaction and moderate the effects of three types of the interaction, self-regulated learning, and Internet self-efficacy variables on student satisfaction? According to the data analysis, there were no main effects of two class-level predictors on student satisfaction. That is, course category and program did not help in the prediction of student satisfaction. Course category was eliminated from the equation in the final model since it did not impact the slope of learner-content interaction. Program, however, did impact the slope of learner-content interaction on student satisfaction but not the slopes of the other four predictors: learner-learner interaction, learner-instructor interaction, Internet self-efficacy, and self-regulated learning. Finally, the three program dummy codes were only entered as level-2 predictors of the slope of learner-content interaction. That is, the level-2 predictor, program, moderated the effect of learner-content interaction on student satisfaction.

Two out of three dummy codes significantly contributed to the effect of learner-content interaction on student satisfaction. Family, Consumer, and Human Development and the Psychology program, which was combined with the program of

Health, Physical Education, and Recreation, were inclined to have a weaker influence on the slope of learner-content interaction in comparison to the program of Instructional Technology and Learning Sciences. No significant difference existed on the effect of the slope of learner-content interaction between the program of Instructional Technology and Learning Sciences and the program of Communicative Disorders and Deaf Education.

Limitations of the Study

Several limitations of this study should be noted. The results of this study were mainly driven from the students in the College of Education and Human Services at Utah State University, which included seven programs. As a land-grant University with an extension and research-extensive mission, classes and resulting experiences may not generalize well to other University settings. The College itself is nationally ranked, excelling in particular at research activity and seeking external research funding. Finally, the college includes a department of Family and Consumer and Human Development, which may diverge from a School or College of Education at similar Universities.

When comparing the number of courses from each program with the number of course offerings, a nonsignificant Chi-square value was found. While this suggests the courses with students responding are representative of the sampling frame, this may not be the case. For instance, students in the program of Instructional Technology and Learning Sciences are from 80% of the available courses; however, students in the program of Communicative Disorders and Deaf Education are from

13% of the available courses. The data may be more representative of students from the program of Instructional Technology and Learning Sciences than those from other programs. Students from this program are more adept in the use of technologies compared to students from other programs within the College of Education. Hence, readers should be cautious about generalizing these results to other education colleges, particularly those without Instructional Technology and Learning Sciences programs.

The return rate, 22.32%, was low, which leads to several consequences. While the minimum number of participants was reached, the results would be more reliable with additional participants. In terms of representativeness of the sample, results were mixed. The distribution of courses from each program with survey responses was similar to the distribution of courses offered based on Chi square analyses. However, the percentage of responding courses against offered courses for each program was unequal, ranging from 13% to 80%. The analysis may be more representative of the courses from the program of Instructional Technology and Learning Sciences than courses with low percentage from other programs. The number of students reveals systematic differences in the sample as compared to the sampling frame. Of the courses with instructor permission, several had fewer than six participants, which may play a role in the lack of statistically significant differences. To meet minimum thresholds for HLM, several courses with limited participation were eliminated. Thus, beyond reliability and representativeness, more participants would improve the HLM model.

This study required online students to fill out the survey based on only one class they selected. Those students who took more than one online course were asked to respond based on just one of their experiences. The issue is that students who took more than one class during the semester might have arbitrarily selected the course they liked most or least, which leads to a bias in the data.

Fully online courses are the focus of this study; hence, the results may only apply to other studies in online learning situation. Courses implemented in blended or hybrid learning environments may lead to more student interaction with the instructor and their fellow students than interaction with the content.

Self-reports are used for the measurement of learner-learner interaction, learner-instructor interaction, and learner-content interaction since self-reports are the most practical method of collecting the data. However, it may mean that not all learner-learner interaction, learner-instructor interaction, and learner-content interaction were captured.

Conclusions and Practical Significance

This research attempted to examine the relationships between five independent variables and student satisfaction, and also to determine the degree to which student satisfaction could be predicted. According to existing literature, there is an array of variables associated with student satisfaction (Barnard et al., 2008; Edvardsson & Oskarsson, 2008; Offir et al., 2007). Considering the number of participants needed for analysis, this study limited the number of predictors to five variables: three types of interaction, Internet self-efficacy, and self-regulated learning. As discussed in the literature review, interaction is a prominent factor to student satisfaction.

Self-regulated learning was found to be significantly related to student satisfaction. Prior research has included variables regarding technology use of students (Rodriguez Robles, 2006). Internet self-efficacy was included since it, to some degree, reveals student perceptions of using technology. Even though some previous studies included demographics as predictors (Abdel-Maksoud, 2007; Rodriguez Robles, 2006), this study did not take them into account.

Consistent with prior research that has shown that interaction is important in distance learning environments (Bray et al., 2008; Chejlyk, 2006; Keeler, 2006; Rodriguez Robles, 2006), the findings of this study have confirmed the importance of interaction in online learning settings.

Learner-content interaction was the strongest predictor that significantly contributed to student satisfaction in online settings, which confirmed the findings of Chejlyk (2006) and Keeler (2006), both of whom determined learner-content interaction was a significant predictor for student satisfaction. However, on the other hand, the results of this research were contrary to some of the prior studies where learner-learner interaction or learner-instructor interaction was found to be the most important predictor in distance learning environments (Battalio, 2007; Bolliger & Martindale, 2004; Jung et al., 2002; Rodriguez Robles, 2006; Thurmond, 2003). In this study, learner-instructor interaction was the second strongest predictor to significantly contribute to student satisfaction.

There are several potential reasons for departures from previous studies on the type of interaction most critical in distance learning environments. Each study result has a different context, which may play a key role in differences between results. The sample consisted of undergraduate and graduate students who participated in fully online courses from the College of Education at a university. Prior research used participants either from a community college or from different subject areas such as business or a mixture of various disciplines, which might lead to different findings. In addition to variations in context, the analyses of interaction were based on different instruments developed by different researchers, which may also result in a varying final result in interaction. Finally, the course format may have been different. Distance learning environments are defined in several different ways including online settings, hybrid settings, or a mixture of the two where the sample in previous studies was driven from one of the cases. When a study is conducted with courses in a hybrid setting, there might be more interactions among learners and between learners and the instructor (Sher, 2004) since face-to-face meetings are available, compared to this study which focuses on fully online courses.

Of all the variations in study design, a common feature in the research and in the findings of this study is that interaction is a consistently strong predictor of student satisfaction. The nature of the interaction may differ from study to study but the overall principle is consistent. This study confirmed Chejlyk’s (2006) findings that learner-content interaction was the most important predictor compared to learner-instructor interaction and learner-learner interaction. Chejlyk’s (2006) study was conducted in a web-based environment where the sample was driven from undergraduates, which was similar to the condition of this study. In addition, this study supported the ideas of Moore (1989) and Kearsley (1996), both of whom highlighted the importance of learner-content interaction in online learning environments in which online learners were provided with a multitude of ways to interact with the content through a variety of technologies offered in a class.

Learner-content interaction was found to be the most critical predictor for student satisfaction in this study. Full online learning environments do not provide face-to-face meetings, which are part of blended or hybrid learning environments. Most of the time, online learners might spend more time on required reading or assignments, and digest the content they need to learn through thinking, elaboration, or reflections, which are internally intellectual communication of a person with the content during learning processes. Instructors and instructional designers should pay attention to organization of the content, document layout, and the ease of accessing online content. A variety of media or technology tools expand opportunities for learner-content interaction (Anderson, 2003). Results in this survey agree, suggesting that embedding interactive videos in the content may be helpful to stimulate student interest or increase motivation to learn. In addition, online content that is related to personal experiences of students may help increase student interaction with course content.

Learner-learner interaction might happen only when certain collaborative activities were required, such as group discussions, group projects, or idea sharing. Interaction between the instructor and learners may happen more often, especially when online learners have questions regarding the course content. Given the weak networking among online learning in a course, the easiest support for online learners may be mainly from the course instructor. That is, more interactions might exist between the instructor and online learners than among learners.

Hence, the finding of this research seemed to make sense where learner-learner interaction was not a significant predictor and had the lowest coefficient among three types of interaction. Learner-instructor interaction was significant in the model with five level-1 predictors, but was not significant in the final model where program was taken into account as a level-2 predictor. This may be due to the fact that significant predictors can become nonsignificant when other predictors were added in, and degrees of freedom are diminished. Nonetheless, learner-instructor interaction was the predictor with the second largest coefficient, following learner-content interaction. Instructors are encouraged to regularly post messages on discussion boards and reply to student questions as soon as possible to increase their interaction with students.

Internet self-efficacy and self-regulated learning were not significant predictors for student satisfaction, corresponding to Rodriguez Robles's (2006) research where Internet self-efficacy did not significantly contributed to student satisfaction. Most students who took online courses in the Fall semester were regular online students and might have possessed a certain level of ability of using the Internet, which may lead to the nonsignificant result. Self-regulated learning was also not a significant predictor for student satisfaction, even though the correlation between self-regulated learning and student satisfaction was significant but very weak.

Depending on the subject matter or the course design, recommendations based on instructional system design may not be applicable to all online courses. The suggestions regarding identifying instructional goals, determining learning outcomes, and selecting the evaluation methods may be applied to each case in online learning situation (Dick et al., 2005). However, some suggestions may not be easily applied in online learning. For instance, a detailed learner characteristics analysis may not be able to be conducted until an online course starts. Selection of delivery method is vital; however, in some situation instructors are forced to use the standard learning management system to deliver the online course.

This is the first study examining the combined effect of three types of interaction, Internet self-efficacy, and self-regulated learning on student satisfaction. There is no doubt that interaction is an important predictor for student satisfaction. Of the studies regarding distance education only a few include Internet self-efficacy, or self-regulated learning as a predictor of student satisfaction. The effect of Internet self-efficacy or self-regulated learning on student satisfaction is inconclusive. By including Internet self-efficacy and self-regulated learning beyond three types of interaction, this study provides more information than previously known. This study not only confirms the importance of interaction in online learning, but also adds to the conflicting findings of the effect of Internet self-efficacy and self-regulated learning on student satisfaction.

None of the prior studies take cluster effects into account when they examine the extent to which independent variables predict student satisfaction in distance learning settings. Instead, prior work relies largely on multiple regression with a disconnected unit of analysis. Students are drawn from several classes but the impact of those classes is not statistically accounted for. This study considers the effect of different classes through the application of HLM techniques. In addition, this study explored the direct and moderator effects of class-level predictor (course category and program) on student satisfaction, which was never done in previous research.

Recommendations for Future Research

This study should be replicated with a more diverse population. The present study only focused on online students from the College of Education. It would be better to include all online students from different disciplines and examine whether learner-content interaction is still the most important predictor for student satisfaction in online settings. Due to the limited number of online students that could be reached in this study, it is suggested that future researchers accumulate data from different semesters, to improve the number of student responses. In addition, other rewarding opportunities such as giving extra credit may be used to increase student responses from each course, which will result in a more reliable finding with HLM analysis.

The three types of interaction measured in this study did not include the influence of teaching assistants. Teaching assistants may play an important role besides the instructor, and online students may have a certain amount of interaction with their teaching assistant. Future research should take into account the influence of teaching assistants on interaction.

Student satisfaction was used as a dependent variable to examine students' perceptions towards online courses. Satisfaction is one of the critical components which can be used in course evaluation. Another assessment approach, such as final grades of an online course, may be added into future studies. When both performance and satisfaction data are collected and investigation of the relationship between the two outcomes can be undertaken.

Some other variables omitted from this study may also influence student satisfaction in online learning environments. Support service, class size, and student autonomy (Biner, Welsh et al., 1997; Rodriguez Robles, 2006; Sahin, 2007) have all been shown to play a role in student satisfaction. Considering the number of participants required depends on the variables in a study, future researchers need to be careful when deciding to add more independent variables.

Four instruments including three types of interaction and student satisfaction were revised based on the instrument used in previous research. Through the pilot study and the content validity survey from professionals, these instruments have proven validity and strong reliability for this sample. Interested researchers can take these instruments and apply them to alternate contexts to improve available data about the validity of these instruments and determine whether or not the reliability holds in other samples.

As noted in Chapter I, HLM were not applied in previous studies of online learning. Future studies attempting to predict student satisfaction with students who have fundamentally different experiences, such as those taking different classes, or attending different institutions are encouraged to take into account any clustering effects, and apply HLM to more accurately model any relationships. Other class-level predictors should also be explored, such as the use of teaching assistants, or the fundamental design of the courses themselves.

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APPENDICES

Appendix A. Enrollments in Summer of 2009

Enrollments in Summer of 2009

Courses		Number of Enrollments
Family, Consumer, and Human Development		
FCHD 3530	Adolescence	13
Instructional Technology & Learning Sciences		
INST 5265/6265	Internet Development	7
INST 6325	Communication, Instruction, and the Learning Process	27
INST 6730	Technology and its Role in the Transformation of Education	22
Communicative Disorders and Deaf Education		
COMD 3500	Phonetics/Developmental Phonology	59
COMD 5070	Speech Science	38
Psychology		
PSY 1400	Analysis Behavior	24
PSY 2800	Psychological Statistics	29
PSY 4420	Cognitive Psychology	8
PSY 6810	Seminar	40
Health, Physical Education, and Recreation		
HEP 3400	Stress Management	24
Total		291

Appendix B. Learner Interaction, Internet Self-Efficacy, Self-Regulated Learning and Satisfaction Survey (For pilot study)

Learner Interaction, Internet Self-Efficacy, Self-Regulated Learning and Satisfaction Survey (For pilot study)

I. Demographics

1. Gender:
   - ☐ Male
   - ☐ Female
2. Marital Status:
   - ☐ Married
   - ☐ Single
3. Age:
   - ☐ 18-25
   - ☐ 26-35
   - ☐ 36-45
   - ☐ 46-55
   - ☐ Above 56
4. You are taking a class at:
   - ☐ undergraduate level (1000-4000)
   - ☐ undergraduate/graduate level (5000)
   - ☐ graduate level (6000+)
5. On average, how many hours do you spend online (on Blackboard) for your course each week?
   - ☐ Less than 5 hours
   - ☐ 6-10 hours
   - ☐ 11-15 hours
   - ☐ 16-20 hours
   - ☐ above 20 hours

II. Interactions

(Please mark the most appropriate number on the scale below each statement.)

Learner-learner interactions:

1. Overall, I had numerous interactions related to the course content with fellow students.
2. I got lots of feedback from my classmates.
3. I communicated with my classmates about the course content through different electronic means, such as email, discussion boards, instant messaging tools, etc.
4. I answered questions of my classmates through different electronic means, such as email, discussion board, instant messaging tools, etc.

5. I shared my thoughts or ideas about the lectures and its application with other students during this class.
6. I comment on other students' thoughts and ideas.
7. Group activities during class gave me chances to interact with my classmates.
8. Class projects led to interactions with my classmates.

(Strongly disagree 1 2 3 4 5 Strongly agree)

Learner-instructor interactions:

1. I had numerous interactions with the instructor during the class.
2. I asked the instructor my questions through different electronic means, such as email, discussion board, instant messaging tools, etc.
3. The instructor regularly posted some questions for students to discuss on the discussion board.
4. The instructor replied my questions in a timely fashion.
5. I replied to messages from the instructor.
6. I received enough feedback from my instructor when I needed it.

(Strongly disagree 1 2 3 4 5 Strongly agree)

Learner-content interactions:

1. Online course materials helped me to understand better the class content.
2. Online course materials stimulated my interest for this course.
3. Online course materials helped relate my personal experience to new concepts or new knowledge.
4. It was easy for me to access the online course materials.

(Strongly disagree 1 2 3 4 5 Strongly agree)

III. Internet self-efficacy

(Please mark the most appropriate number on the scale below each statement.)

I feel confident:

1. understanding terms/words relating to Internet hardware.
2. understanding terms/words relating to Internet software.
3. describing functions of Internet hardware.
4. trouble shooting Internet hardware.
5. explaining why a task will not run on the Internet.
6. using the Internet to gather data.
7. confident learning advanced skills within a specific Internet program.
8. turning to an on-line discussion group when help is needed.

(Very unlikely 1 2 3 4 5 6 7 Very likely)

IV. Self-Regulated Learning

(Please mark the most appropriate number on the scale below each statement.)

1. During class time I often miss important points because I'm thinking of other things.
2. When reading for this course, I make up questions to help focus my reading.
3. When I become confused about something I'm reading for this class, I go back and try to figure it out.
4. If course materials are difficult to understand, I change the way I read the material.
5. Before I study new course material thoroughly, I often skim it to see how it is organized.
6. I ask myself questions to make sure I understand the material I have been studying in this class.
7. I try to change the way I study in order to fit the course requirements and instructor's teaching style.
8. I often find that I have been reading for class but don't know what it was all about.
9. I try to think through a topic and decide what I am supposed to learn from it rather than just reading it over when studying.
10. When studying for this course I try to determine which concepts I don't understand well.
11. When I study for this class, I set goals for myself in order to direct my activities in each study period.
12. If I get confused taking notes in class, I make sure I sort it out afterwards.

(Not at all true of me 1 2 3 4 5 6 7 Very true of me)

V. Satisfaction

(Please mark the most appropriate number on the scale below each statement.)

1. Overall, I am satisfied with this class.
2. This course contributed to my educational development.
3. This course contributed to my professional development.
4. I am satisfied with the level of interaction that happened in this course.
5. In the future, I would be willing to take a fully online course again.

(Strongly disagree 1 2 3 4 5 Strongly agree)

Appendix C. Content Validity Survey for Interaction and Satisfaction Scales

Content validity survey for "Interaction" and "Satisfaction" scales

Dear Professors,
I am working on my proposal, and require content validity information for three "Interaction" scales and a "Satisfaction" scale. These scales will be given to students who take USU online courses. I need your help to rate the items on all four scales to determine if the items are adequate for the specific domain / content area that they are supposed to measure. Content validity ratio (CVR) will be calculated based on the ratings that you give.
Please read each item carefully and determine whether and to what degree it assesses, in your expert opinion, the specific content domain it is supposed to measure.
For each item, please select one of three choices:

- "essential,"
- "useful but not essential," or
- "neither essential nor useful."

Please mark the most appropriate choice for each item.

Please notice: I will have 6 experts rate these items for me, which is a very small sample. In the case of 6 panelists, an item would need **a minimum CVR of .99.** That means that *if 6 out of 6 experts rate the same item as essential or at least as useful, the minimum CVR ".99" can be reached and the item will be maintained in the scale.* If any one out of 6 raters rates the item as "neither useful nor essential," then the item will not be kept in the scale.

Thanks for your great help~!

Yu-Chun Kuo

Background information / content domain description for interaction and satisfaction:

A. Interaction: The most popular framework of interaction in distance education is proposed by Moore (1989), in which three major constituents are included: learner-instructor interaction, learner-learner interaction, and learner-content interaction. *Learner-instructor interaction* refers to a two-way communication between the instructor of the course and learners. *Learner-learner interaction* involves a two-way reciprocal communication between or among learners with their fellow students, with or without the presence of an instructor.

Learner-content interaction refers to a non-human interaction learners have with the subject matter or the course content.

B. Satisfaction: Satisfaction is considered as part of the evaluation of distance courses. Student satisfaction is an important indicator of the effectiveness of a course, and is critical to the success of distance programs (Allen & Seaman, 2003; Biner, Welsh, Barone, Summers & Dean, 1997; Keller, 1987). Satisfaction in this study is defined as student's perception related to learning experiences and perceived value of an online course.

Part I:

Interaction scale: This instrument is a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

1. Overall, do you think that the items in interaction are well designed?

   ☐ Yes ☐ Not sure (Please specify:______________________________________)

2. Please mark the most appropriate choice for each item:

No.		essential	useful but not essential	neither essential nor useful
Learner-learner interaction				
1	Overall, I had numerous interactions related to the course content with fellow students.			
2	I usually communicated with my classmates through instant messaging tools, such as Wimba, Blackboard chat rooms, MSN, Skype, Yahoo Messenger, etc.			
3	I got lots of feedback from my classmates.			
4	Online discussion boards gave me opportunities to communicate with my fellow students.			
5	I usually interacted with my classmates through email.			
6	I usually got feedback from my classmates through the discussion board on Blackboard.			
7	I usually answered questions of my classmates through the discussion board.			
8	I often shared my thoughts or ideas about the lectures and its application with other students			

	during this class.			
9	I often comment on other students' thoughts and ideas.			
10	Group activities during class gave me chances to interact with my classmates.			
11	Class projects led to interactions with my classmates.			
Learner-instructor interaction				
12	I had numerous interactions with the instructor during the class.			
13	I usually e-mailed the instructor with the questions that I had.			
14	I usually asked the instructor my questions through instant messaging tools, such as Wimba, Blackboard chat rooms, MSN, Skype, Yahoo Messenger, etc.			
15	I usually asked the instructor my questions through the discussion board.			
16	The instructor regularly posted some questions for students to discuss on the discussion board.			
17	The instructor often replied my questions in a timely fashion.			
18	I often replied to messages from the instructor.			
19	I received enough feedback from my instructor when I needed it.			
20	The instructor encouraged us to question different ideas and perspectives.			
21	The instructor aroused my interest in some issues, which motivated me to learn more.			
Learner-content interaction				
22	Online course materials helped me to understand better the class content.			
23	Online course materials stimulated my interest for this course.			
24	Online course materials helped relate my personal experience to new concepts or new knowledge.			
25	I spent lots of time going over the course			

	materials.			
26	I often looked at other online resources as a supplement to the course materials.			
27	It was easy for me to access the online course materials.			

3. Are there any critical aspects missing or do you have questions or comments on specific items? If so, please indicate the number of item, and write down your thoughts (suggested wording changes, concerns about “double barreled items”, etc . . .) here:______________

____

______

Part II:

Satisfaction scale: This instrument is a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

1. Overall, do you think that the items in satisfaction scale are well designed?
   ☐ Yes ☐ Not sure (Please specify:____)
2. Please mark the most appropriate choice for each item:

No.		essential	useful but not essential	neither essential nor useful
1	Overall, I am satisfied with this class.			
2	The course was a useful learning experience to me.			
3	This course contributed to my personal development.			
4	This course contributed to my educational development.			
5	This course contributed to my professional development.			
6	I am satisfied with the level of interaction that happened in this course.			
7	In the future, I would be willing to take a fully			

	online course again.			

3. Are there any critical aspects missing or do you have questions or comments on specific items? If so, please indicate the number of item, and write down your thoughts (suggested wording changes, concerns about “double barreled items”, etc . . .) here:______________

____

Appendix D. Learner Interaction, Internet Self-Efficacy, Self-Regulated Learning and Satisfaction Survey

Learner Interaction, Internet Self-Efficacy, Self-Regulated Learning and Satisfaction Survey

If you are taking multiple online courses from the College of Education, please select only one class, filling out the survey based on your experiences in that class alone.

I. Demographics

1. Gender:
   - ☐ Male
   - ☐ Female
2. Marital Status:
   - ☐ Married
   - ☐ Single
3. Age:
   - ☐ 18-25
   - ☐ 26-35
   - ☐ 36-45
   - ☐ 46-55
   - ☐ Above 56

For Questions 4-6, please specify the course you are taking and the instructor who is teaching it:

4. Course number (for instance: EDUC 1000):______________________
5. Course title (for instance: Learning Theory):______________________
6. Instructor name (for instance: Mark Lee):______________________
7. On average, how many hours do you spend online (on Blackboard) for your course each week?
   - ☐ Less than 5 hours
   - ☐ 6-10 hours
   - ☐ 11-15 hours
   - ☐ 16-20 hours
   - ☐ above 20 hours

II. Interactions

(Please mark the most appropriate number on the scale below each statement.)
Learner-learner interactions:
1. Overall, I had numerous interactions related to the course content with fellow students.
2. I got lots of feedback from my classmates.
3. I communicated with my classmates about the course content through different electronic means, such as email, discussion boards, instant messaging tools, etc.
4. I answered questions of my classmates through different electronic means, such as email, discussion board, instant messaging tools, etc.
5. I shared my thoughts or ideas about the lectures and its application with other students during this class.
6. I comment on other students' thoughts and ideas.
7. Group activities during class gave me chances to interact with my classmates.
8. Class projects led to interactions with my classmates.

(Strongly disagree 1 2 3 4 5 Strongly agree)

Learner-instructor interactions:
1. I had numerous interactions with the instructor during the class.
2. I asked the instructor my questions through different electronic means, such as email, discussion board, instant messaging tools, etc.
3. The instructor regularly posted some questions for students to discuss on the discussion board.
4. The instructor replied my questions in a timely fashion.
5. I replied to messages from the instructor.
6. I received enough feedback from my instructor when I needed it.

(Strongly disagree 1 2 3 4 5 Strongly agree)

Learner-content interactions:
1. Online course materials helped me to understand better the class content.
2. Online course materials stimulated my interest for this course.
3. Online course materials helped relate my personal experience to new concepts or new knowledge.
4. It was easy for me to access the online course materials.

(Strongly disagree 1 2 3 4 5 Strongly agree)

III. Internet self-efficacy
(Please mark the most appropriate number on the scale below each statement.)
I feel confident:

1. understanding terms/words relating to Internet hardware.
2. understanding terms/words relating to Internet software.
3. describing functions of Internet hardware.
4. trouble shooting Internet hardware.
5. explaining why a task will not run on the Internet.
6. using the Internet to gather data.
7. confident learning advanced skills within a specific Internet program.
8. turning to an on-line discussion group when help is needed.

(Very unlikely 1 2 3 4 5 6 7 Very likely)

IV. Self-Regulated Learning

(Please mark the most appropriate number on the scale below each statement.)

13. During class time I often miss important points because I'm thinking of other things.
14. When reading for this course, I make up questions to help focus my reading.
15. When I become confused about something I'm reading for this class, I go back and try to figure it out.
16. If course materials are difficult to understand, I change the way I read the material.
17. Before I study new course material thoroughly, I often skim it to see how it is organized.
18. I ask myself questions to make sure I understand the material I have been studying in this class.
19. I try to change the way I study in order to fit the course requirements and instructor's teaching style.
20. I often find that I have been reading for class but don't know what it was all about.
21. I try to think through a topic and decide what I am supposed to learn from it rather than just reading it over when studying.
22. When studying for this course I try to determine which concepts I don't understand well.
23. When I study for this class, I set goals for myself in order to direct my activities in each study period.
24. If I get confused taking notes in class, I make sure I sort it out afterwards.

(Not at all true of me 1 2 3 4 5 6 7 Very true of me)

V. Satisfaction

(Please mark the most appropriate number on the scale below each statement.)

1. Overall, I am satisfied with this class.

2. This course contributed to my educational development.
3. This course contributed to my professional development.
4. I am satisfied with the level of interaction that happened in this course.
5. In the future, I would be willing to take a fully online course again.

(Strongly disagree 1 2 3 4 5 Strongly agree)

Appendix E. Recruitment Letter (for instructors)

Recruitment Letter (for instructors)

Dear colleague,

We are currently conducting a research study on the effects of student interaction, Internet self-efficacy, and self-regulated learning on student satisfaction in distance learning environments. This study has been reviewed and approved by the Institutional Review Board of Utah State University and we are now looking for students enrolled in distance courses which are:

1. In the College of Education and Human Services areas.
2. Delivered entirely online.
3. At the undergraduate or graduate level.

You are being contacted now because of your affiliation as an instructor of the distance course(s) which fit our criteria. We would appreciate it if you could inform your students about our online survey, or include our online survey link in your Blackboard course(s).

If you are interested in participating in this survey, please help forward the survey link (http://tinyurl.com/l6dy9n) to your students by the Blackboard email system or by any mechanisms that you normally use to communicate with your students (for example: via a Blackboard announcement, in a Blackboard discussion thread, or through some alternative means). In addition, please email us and let us know if you have passed the online survey link on to your students. Attached please find a copy of informed consent and a sample of the survey students would be asked to complete. Upon request we have a more detailed proposal you are more than welcome to review.

The survey itself would be delivered via SurveyMonkey tool in which student responses are stored anonymously. Students (including those who initiate but do not complete the survey) would be eligible for a $100 gift card drawing.

We feel that the effort on your part would be minimal. If you are interested in participating or have any questions about this study, please contact me directly via email andy.walker@usu.edu or by phone 7-2614. We would also be happy to share our research result with you.

We look forward to hearing from you.

Best Regards,

Andrew Walker Yu-Chun Kuo
Assistant Professor Doctoral Student
Department of Instructional Technology and Learning Sciences

Appendix F. Recruitment Letter (for students)

Recruitment Letter (for students)

Dear students,

We are currently conducting a research study on the effects of student interaction, Internet self-efficacy, and self-regulated learning on student satisfaction in distance learning environments. This study has been reviewed and approved by the Institutional Review Board of Utah State University. You have been selected because you are taking a distance course which is:

1. In the College of Education and Human Services areas.
2. Delivered entirely online.
3. At either the undergraduate or graduate level.

We have received permission from your instructor to have you participate in this online survey (http://tinyurl.com/l6dy9n). Participation in this research is voluntary and, before completing the survey, you will be asked to read and electronically sign (accept) an Informed Consent. The survey will require about twenty minutes of your time. All students who initiate the survey will be eligible for a drawing for a $100 gift card. We would appreciate your filling out the online survey, and would be happy to share the result of our study with you.

If you have any questions, please feel free to contact us at andy.walker@usu.edu or yuchun.kuo@aggiemail.usu.edu. We appreciate your assistance.

Best Regards,

Andrew Walker | Yu-Chun Kuo
Assistant Professor | Doctoral Student
Instructional Technology and Learning Sciences

Appendix G. Enrollments of the Full Study

Enrollments of the Full Study

Courses		Number of Enrollments	Number of student survey responses
Instructional Technology & Learning Sciences			
INST 5120/6120	Distance Education Projects	7	3
INST 5140/6140	Producing Distance Education Resources	21	7
INST 6310	Foundations of Educational Technology	27	12
INST 6325	Communication, Instruction, & the Learning Process	29	7
INST 6760	Grant Writing	19	No permission
Communicative Disorders and Deaf Education			
COMD 2500	Language, Speech, & Hearing Development	144	No permission
COMD 2910	Sign Language I (CI)- section 1	20	2
COMD 2910	Sign Language I (CI)- section 2	6	No permission
COMD 3100	Fundamentals of Anatomy for Speech & Language	168	No permission
COMD 3120	Disorders of Articulation & Phonology	66	9
COMD 3300/6500	Introduction to Blindness & Visual Impairment/ Studies in Blindness & Visual Impairment	13	No permission
COMD 3320/6520	The Human Eye & Visual System/ Anatomy, Function, & Disorders of the Eye	6	No permission
COMD 3340	The Role of Paraeducators	13	No permission

Courses		Number of Enrollments	Number of student survey responses
COMD 3400	Acoustics & Anatomy of the Ear	71	No permission
COMD 3500	Phonetics/Developmental Phonology	108	No permission
COMD 3700	Basic Audiology	50	No permission
COMD 3910	Sign Language II	2	No permission
COMD 4250	Cooperative Practicum/Work Experience	1	No permission
COMD 4450	Assessment & Treatment of Communicative Disorders in the Pediatric Population	40	No permission
COMD 4660/6660	Introduction to Deaf-Blindness/ Introduction to Deaf-Blindness	27	No permission
COMD 5070	Speech Science	51	3
COMD 5100	Language Science	81	No permission
COMD 5200*	Language Assessment & Intervention for Children Birth to Age Five	18	No permission
COMD 5200*	Language Assessment & Intervention for Children Birth to Age Five	14	No permission
COMD 5330	Pediatric Aural Rehabilitation	40	No permission
COMD 5900	Independent Study	40	No permission
COMD 3360/6560	Beginning Braille in the Classroom/ Braille	10	No permission
COMD 7340	Pediatric Audiology	2	No permission
Family, Consumer, and Human Development			
FCHD 1010	Balancing Work & Family (BSS)	84	16

Courses		Number of Enrollments	Number of student survey responses
FCHD 1100	Critical Issues in Family, Consumer, & Human Development	13	No permission
FCHD 1500	Human Development Across the Lifespan (BSS)	91	No permission
FCHD 2100	Family Resource Management	35	2
FCHD 2400	Marriage & Family Relationships (BSS)	51	No permission
FCHD 2450	The Consumer & the Market (BSS)	29	No permission
FCHD 2610	Child Guidance	63	17
FCHD 3100	Abuse & Neglect in Family Context	39	2
FCHD 3280	Economic Issues for Individuals & Families	11	No permission
FCHD 3340	Housing: Societal & Environmental Issues	12	No permission
FCHD 3350	Family Finance (DSS)	129	31
FCHD 3450	Consumer Credit Problems	17	No permission
FCHD 3510	Infancy & Early Childhood	29	4
FCHD 3520	Children in the Middle Years	25	No permission
FCHD 3530	Adolescence	26	6
FCHD 4220	Family Crises & Interventions	23	2
FCHD 4230	Families and Social Policy	19	4
FCHD 4240	Social & Family Gerontology	10	No permission
FCHD 4820	Current Issues in Family Life Studies	6	No permission
FCHD 4830	Senior Capstone Project	5	No permission
Psychology			

Courses		Number of Enrollments	Number of student survey responses
PSY 1010	General Psychology (BSS)	86	No permission
PSY 1100	Developmental Psychology: Infancy & Childhood	38	No permission
PSY 1210	Human Adjustment	10	No permission
PSY 1220	Career & Life Planning	21	No permission
PSY 1400	Analysis of Behavior: Basic Principles	36	6
PSY 1410	Analysis of Behavior: Basic Principles Lab	36	No permission
PSY 1730	Strategies for Academic Success	12	No permission
PSY 2100	Developmental Psychology: Adolescence	13	No permission
PSY 2800	Psychological Statistics (QI)	31	21
PSY 2950	Orientation to Psychology as a Career & Profession	28	3
PSY 3120	Abuse, Neglect, & the Psychological Dimensions of Intimate Violence (DSS)	35	No permission
PSY 3210	Abnormal Psychology (DSS)	36	No permission
PSY 3400	Analysis of Behavior: Advanced (DSS)	7	No permission
PSY 3460	Physiological Psychology	24	2
PSY 3500	Scientific Thinking & Methods in Psychology (DSS/CI)	22	4
PSY 3510	Social Psychology (DSS)	27	No permission
PSY 3660	Educational Psychology for Teachers	7	No permission
PSY 3720	Behavior Modification	1	No permission
PSY 4210	Personality Theory (DSS)	8	No permission

Courses		**Number of Enrollments**	**Number of student survey responses**
PSY 4230	Psychology of Gender (DSS)	11	No permission
PSY 4240	Multicultural Psychology (DSS)	1	No permission
PSY 4420	Cognitive Psychology (DSS)	16	2
PSY 4430	Cognitive Psychology Lab	16	No permission
PSY 4510	Effective Social Skills Interventions (CI)	4	No permission
PSY 4950	Undergraduate Apprenticeship (CI)	17	No permission
PSY 4960	Advanced Undergraduate Apprenticeship (CI)	1	No permission
PSY 5050	Psychological Aspects of Sports Performance	3	No permission
PSY 5100	History & Systems of Psychology	16	No permission
PSY 5200	Introduction to Interviewing & Counseling (CI)	14	No permission
PSY 5330	Psychometrics	11	4
Special Education and Rehabilitation			
SPED 1010	Society & Disability (BSS)	7	No permission
SPED 4000	Education of Exceptional Individuals	45	6
REH 1010	Society & Disability (BSS)	7	No permission
School of Teacher Education & Leadership (Elementary/Secondary Education)			
TEAL 6100	Motivation & Management in Inclusive Settings	22	No permission
ELED 3000	Foundation Studies & Practicum in Teaching & Classroom Management Level II (CI)	15	3
Health, Physical Education, and Recreation			

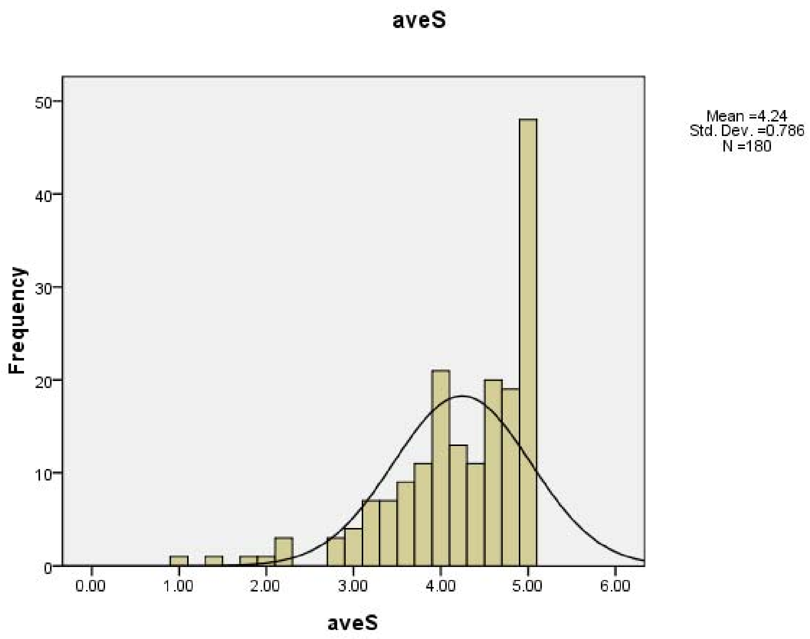
Courses		Number of Enrollments	Number of student survey responses
PE 3000	Dynamic Fitness	43	No permission
HEP 2500	Health and Wellness	32	No permission
HEP 3000	Drugs and Human Behavior	34	2
HEP 3200	Consumer Health	24	No permission
HEP 3400	Stress Management	39	No permission
Total		2668	221

No permission: The courses without instructors' permission of distributing the online survey

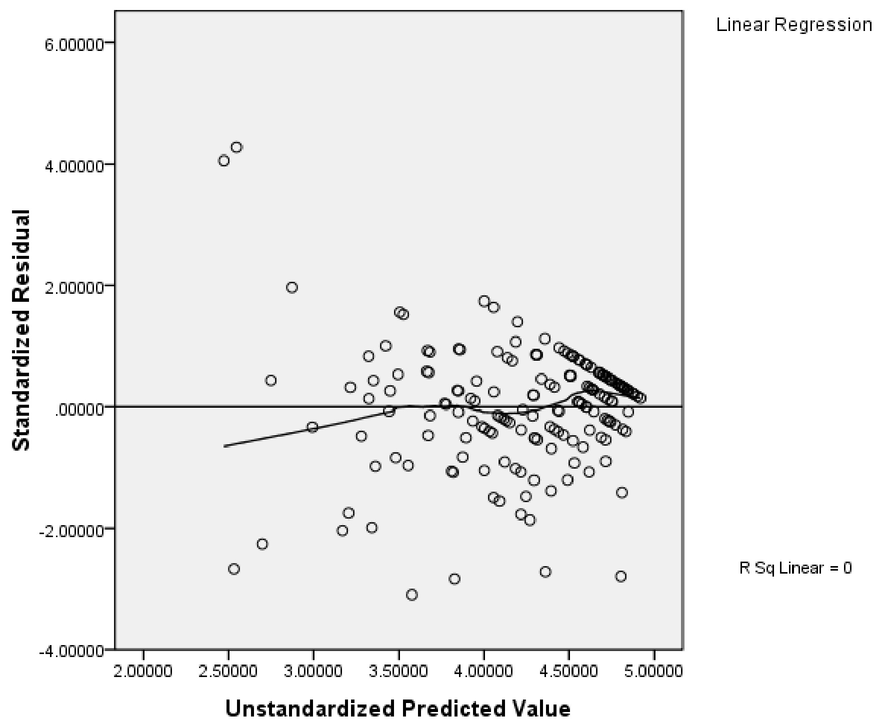
Appendix H. Regression Diagnosis Plots

Regression Diagnosis Plots

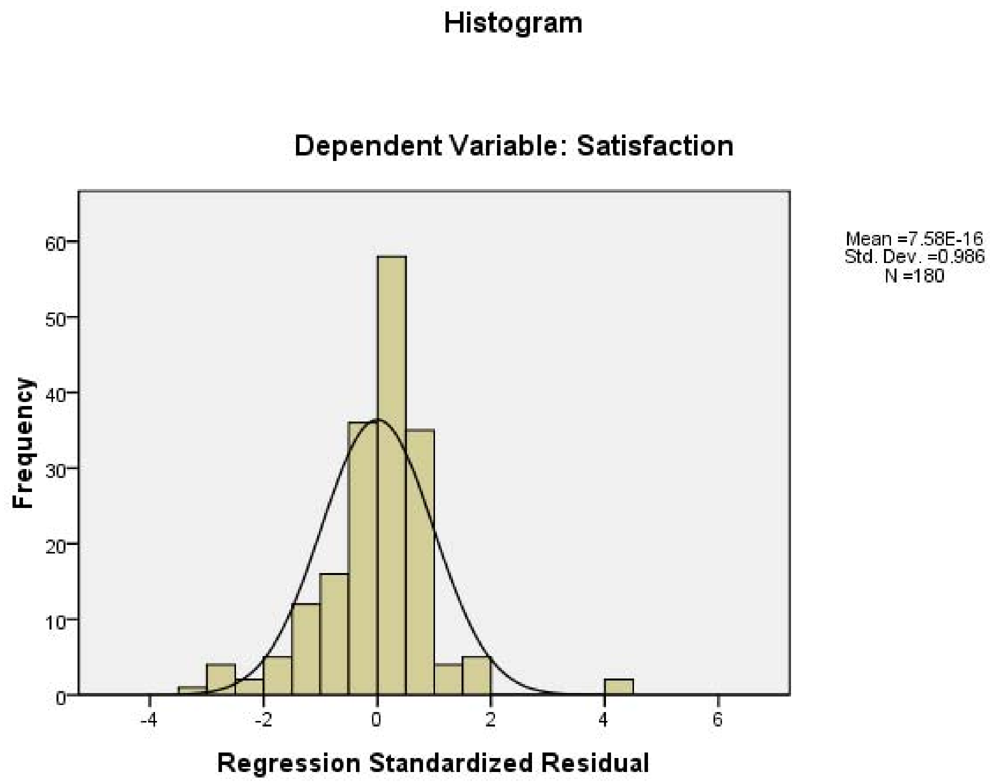
1. Distribution of the dependent variable



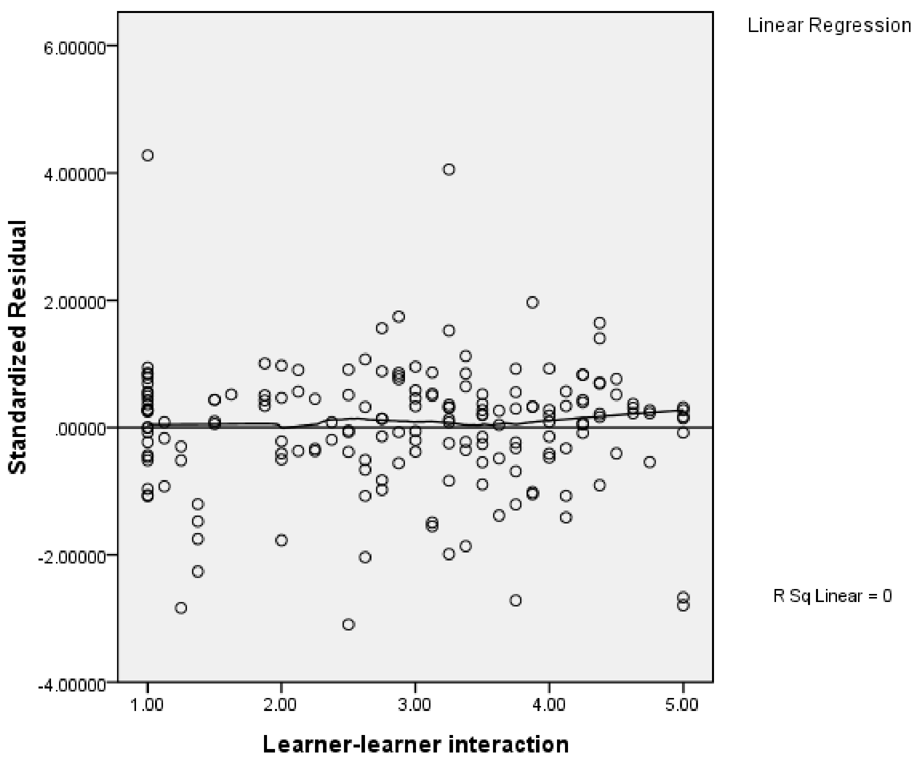
2. The scatterplot of the predicted value against residuals

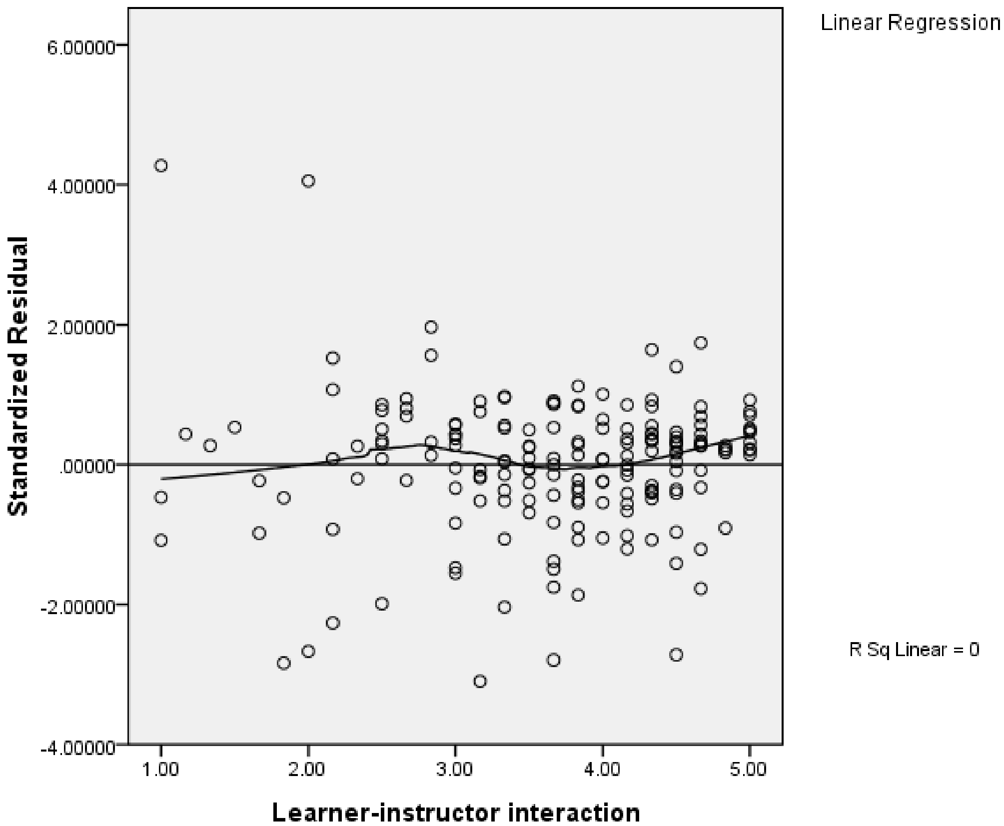


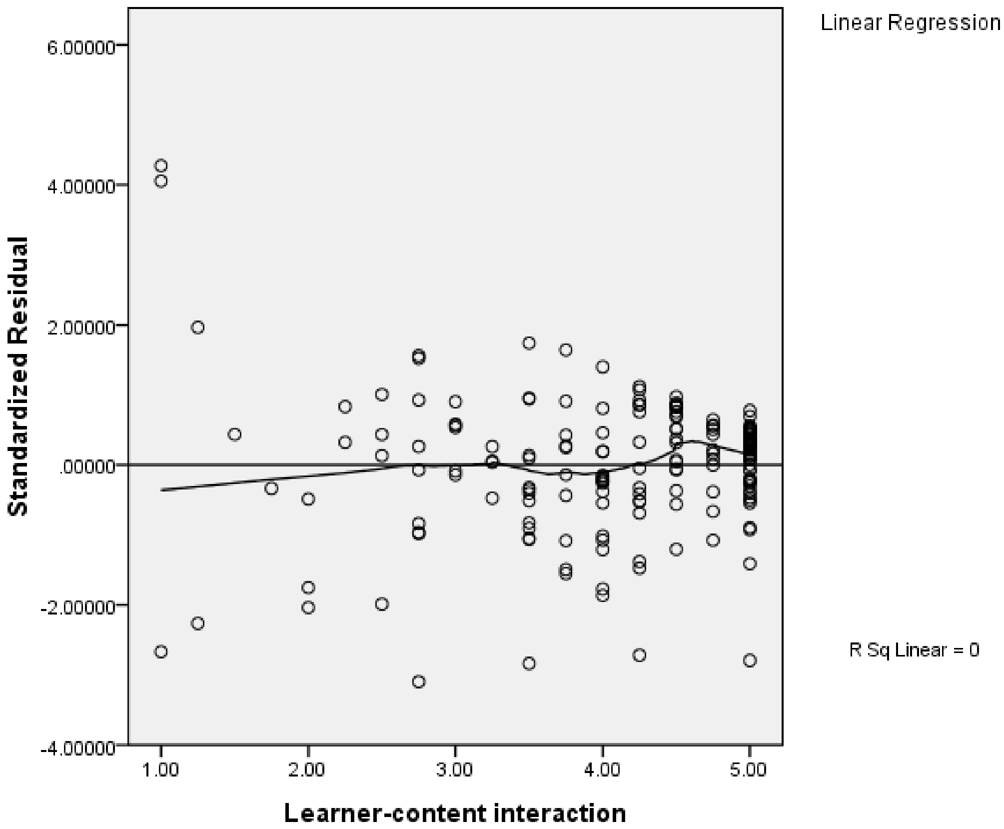
3. The histogram of the frequency of standardized residuals

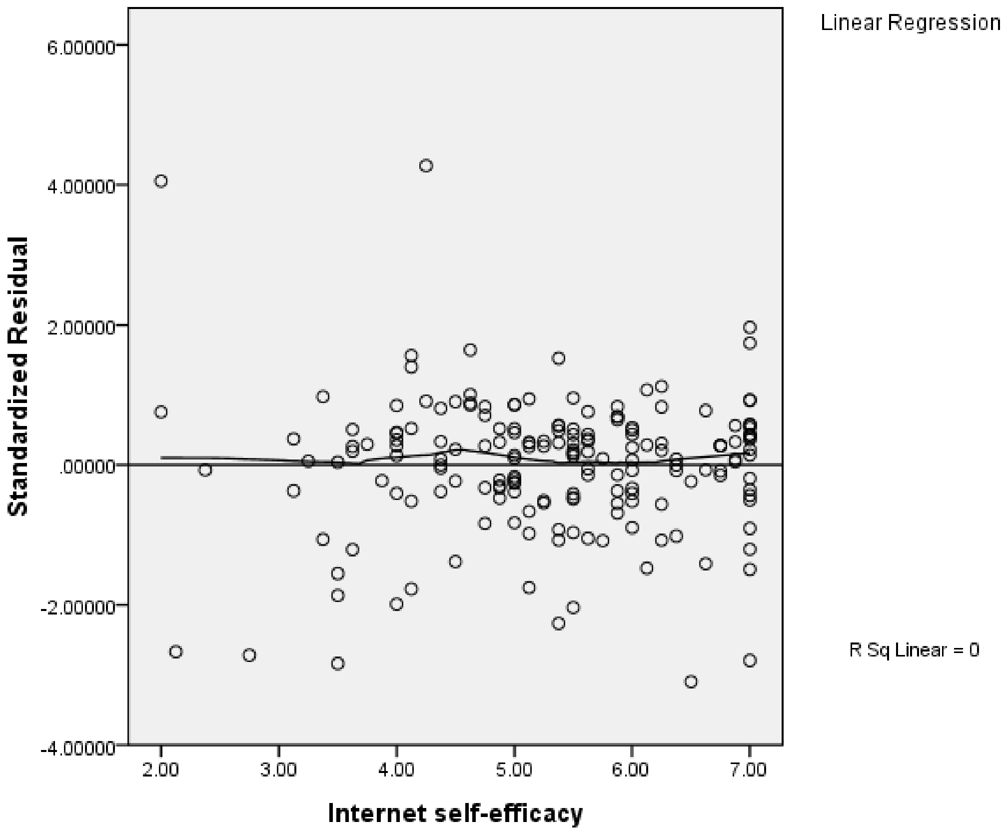


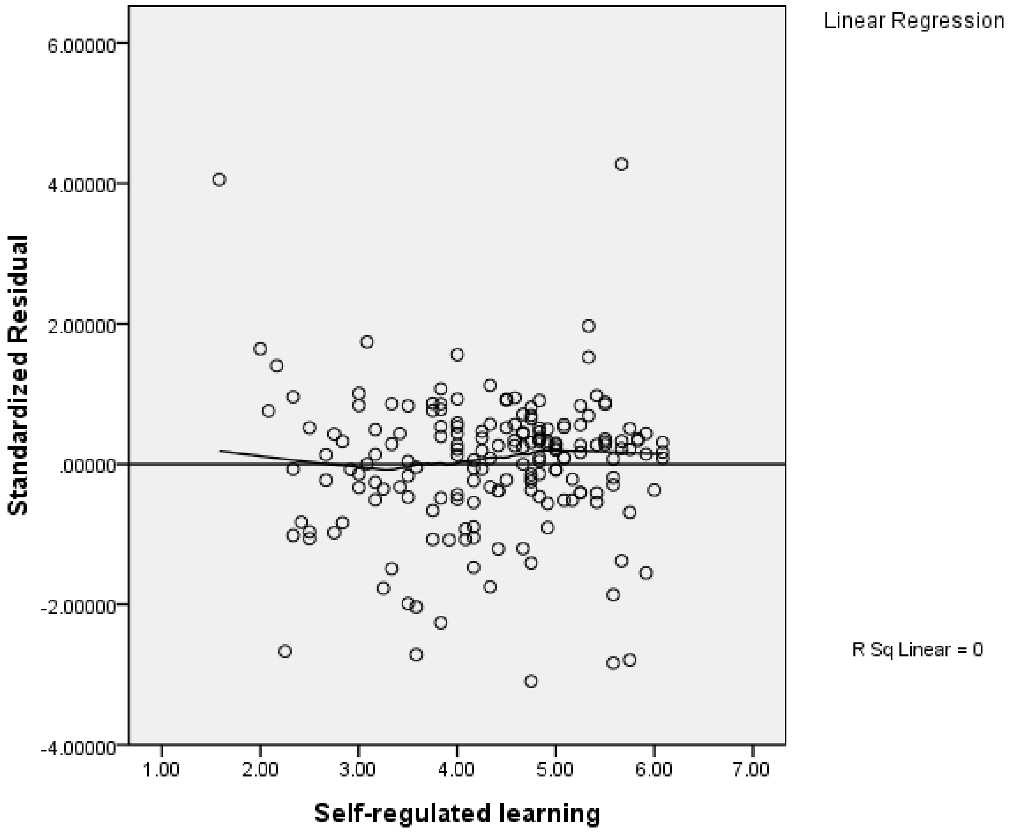
4. The scatterplots of independent variables against residuals




Linear Regression
6.00000
4.00000
2.00000
.00000
-2.00000
-4.00000
Standardized Residual
1.00
2.00
3.00
4.00
5.00
Learner-instructor interaction
R Sq Linear = 0


Linear Regression
R Sq Linear = 0
Standardized Residual
6.00000
4.00000
2.00000
.00000
-2.00000
-4.00000
1.00
2.00
3.00
4.00
5.00
Learner-content interaction


Linear Regression
R Sq Linear = 0
Standardized Residual
6.00000
4.00000
2.00000
.00000
-2.00000
-4.00000
2.00
3.00
4.00
5.00
6.00
7.00
Internet self-efficacy


Linear Regression
6.00000
4.00000
2.00000
.00000
-2.00000
-4.00000
Standardized Residual
1.00
2.00
3.00
4.00
5.00
6.00
7.00
Self-regulated learning
R Sq Linear = 0

5. The histogram of Centered Leverage Value