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Enhancing Educational Dialogue to Promote Student Successin an Online Independent Study Statistics Course

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in an Online Independent Study Statistics Course

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A dissertation submitted to the faculty of
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Doctor of Philosophy

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ABSTRACT

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in an Online Independent Study Statistics Course

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This two-article dissertation examined the impact of enhanced educational dialogue, in terms of periodic email feedback on course progress and an invitation to participate in a discussion board, on student achievement and course satisfaction in an introductory statistics course offered in an independent study setting. Participants in the study were students enrolled in the year-long online course. They were randomly assigned to different types and levels of educational dialogue and their completion status, final exam scores, average quiz scores, and course satisfaction ratings were compared after controlling for the following covariates of interest: age, gender, high school GPA, Math ACT, learner autonomy, attitude on the usefulness of statistics, and confidence in learning statistics. The different types and levels of educational dialogue used in this study were: email reminders only, discussion board only, email and discussion board, and no email or discussion board.

Successful completion of introductory statistics courses in online learning environments can be predicted by student's attitude toward statistics and learner autonomy, in addition to the conventional measures of mathematics aptitude (ACT Math score) and effort as measured by High School GPA; however, there is a scarcity of psychometrically sound and brief measures of these constructs. The first article developed and validated the following scales as measures of attitude toward statistics and learner autonomy: perceived value of statistics (4 items), confidence in learning statistics (4 items), and learner autonomy (3 items). These abbreviated scales are shown to have content and discriminant validity. They can be used by statistics education researchers with confidence.

The second article used MANCOVA and logistic regression to analyze the data collected from the randomized controlled experiment. The MANCOVA results show that students who have higher confidence in learning statistics have higher final exam scores and higher course satisfaction at the 5% level of significance. In addition, students assigned to the email group have the highest average quiz scores. Logistic regression results show that older students and those who have high confidence in learning statistics are more likely to complete the course. Overall, the completion rate for this study is significantly higher than the previous sections of the course. One of the implications of this study is that basic course progress feedback to students with minimal teacher-student interaction may have a beneficial impact on student achievement in online courses.

Keywords: instructional dialogue, course progress feedback, learner autonomy, course satisfaction, student achievement

ACKNOWLEDGMENTS

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DESCRIPTION OF RESEARCH AGENDA AND STRUCTURE OF DISSERTATION

This dissertation report examines the impact of enhanced educational dialogue in an introductory statistics course for undergraduate students in an online, independent study setting. This statistics course would satisfy the quantitative reasoning and advanced language requirements of general education in most colleges and universities. The course, with a maximum duration of 15 months, has an average annual enrollment of at least 1,000 students spread across the continental United States, Europe, and Asia. The historical completion rate for this course is about 51% with an 85% passing rate for those who completed the course. The authors sought to improve the completion and passing rates for this course by increasing educational dialogue through the use of reminder emails based on student quiz completion and quiz scores and by an invitation to participate in an online discussion board based on topics chosen by the instructor.

The goal of this study was to improve completion rate, passing rate, and course satisfaction for students enrolled in an independent study introductory statistics course. A randomized, controlled, and double-blinded experiment was designed in which the two interventions consisted of regular email reminders and invitation to participate in a discussion board. In addition, predictors of student success in online learning environments (e.g., gender, age, previous math and school achievement, attitude towards statistics, and learner autonomy) were added as covariates to obtain a more precise estimate of the treatment effects; however, some of these predictor variables involved scales like attitude towards statistics and learner autonomy which lacked sound psychometric properties and consisted of numerous items. The principal investigator needed reliable and abbreviated scales for these predictor variables. Thus, the first article deals with the construction and validation of these new shortened scales.

This dissertation combines the traditional dissertation requirements with journal publication formats. It is presented as two journal-ready articles and conforms to length and style requirements for submitting research reports to statistics education research journals. The first article is titled *Development and Evaluation of Abbreviated Scales for Attitude Towards Statistics and Learner Autonomy*. Data came from a pre-course survey consisting of questions designed to measure the student's attitudes toward statistics and their level of learner autonomy. The data set was randomly divided into two halves. The first half was analyzed using exploratory factor analysis (EFA) and the second half was analyzed using confirmatory factor analysis (CFA) to cross-validate the EFA results. Widely used recommendations was used for optimal scale development involving factor analysis (Fabrigar & Wegener, 2012; Harrington, 2009; Worthington & Whittaker, 2006) to determine how many factors to extract, what items to keep, and what measurement model to use. The EFA and CFA results showed that these abbreviated scales had psychometric properties in the good range notwithstanding their brevity. I am planning to submit this article to the Journal of Behavioral and Educational Statistics. Richard R Sudweeks, the second author of this article, provided advice on the content validity of the scales on attitude towards statistics and learner autonomy. He oversaw the cross-validation of the EFA and CFA results and the write-up of the research findings.

The second article is titled *Enhancing Educational Dialogue to Promote Student Success in an Independent Study Statistics Course*. It examined the impact of enhanced educational dialogue on student performance and satisfaction. Enhanced educational dialogue consisted of sending periodic email reminders, study tips, and encouragement from the instructor based on student's quiz completion and scores, and inviting students to participate in an online discussion board based on topics deemed by the instructor to be essential in achieving the course's learning

outcomes. Students who agreed to participate in the study were randomly assigned to four

treatment groups: current course or control group, email group, discussion board, and the email

and discussion board group. The outcome variables in the study were completion rate, average

quiz score, final exam score, and course satisfaction rating derived from a post-course survey.

The control variables used were age, gender, previous academic achievement, learner autonomy,

and attitude towards statistics. Measures for attitude towards statistics and learner autonomy

were obtained from a pre-course survey given immediately after students registered for the

course. I am planning to submit this article to the Journal of Statistics Education. The second

co-author, Del T. Scott, helped design and implement the randomized, controlled experiment on

the Moodle course website.

These two articles used the same data set derived from the randomized controlled

experiment involving students enrolled in the independent study statistics course of a large

private university in the western United States from August 2013 to February 2016. They are

formatted for journal submission and references are provided at the end of each article.

This dissertation includes six appendices. Appendix A contains an extended literature

review. Appendix B contains the three email templates sent to students who satisfied the

following conditions:

- those who have completed at least three credit quizzes in a week and obtained at

  least 85% in each quiz,

- those who have not submitted any quiz for two weeks, or

- those who have been getting less than 65% on their last six quizzes.

Appendix C consists of the nine questions posted on the discussion board and the invitation sent

to students to participate. Appendix D contains the questions in the course satisfaction survey

that was given to students who completed the course. Appendix E contains the 13 questions

asked in the pre-course survey to measure attitude towards statistics and learner autonomy.

Appendix F contains a copy of the IRB stamp of approval and statement of implied consent by

the research participants.

Article #1: Development and Evaluation of Abbreviated Scales for Attitude Towards

Statistics and Learner Autonomy

Development and Evaluation of Abbreviated Scales for Attitude Towards

Statistics and Learner Autonomy

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Abstract

Student performance in introductory statistics courses in online learning environments can be predicted by students' attitudes toward statistics and learner autonomy; however, there is a scarcity of psychometrically sound and abbreviated measures of these constructs. This study developed and validated measures of student's perception of the usefulness of statistics, confidence in learning statistics, and learner autonomy using exploratory and confirmatory factor analyses. These three scales possess solid psychometric properties of validity and reliability. Researchers can confidently use them in their future studies. Scale developers can also create adequate scales with no mix of positive and negative items, with at least three items, and at least six response options.

Keywords: scale development, scale validation, statistics education, attitude towards statistics, learner autonomy

Development and Evaluation of Abbreviated Scales for Attitude Towards

Statistics and Learner Autonomy

Student performance in introductory statistics courses in online learning environments can be predicted by students' attitudes toward statistics and learner autonomy, in addition to the conventional measures of mathematics aptitude. In statistics education research, past studies have shown a relationship between attitudes toward statistics and student achievement (Bending & Hughes, 1954; Budé et al., 2007; Hilton, Schau, & Olsen, 2004; Vanhoof, Kuppens, Sotos, Verschaffel, & Onghena, 2011; Williams, 2015). As a result, numerous measures of attitude towards statistics have been developed starting in the 1950s. Nolan, Beran, and Hecker (2012) examined all peer-reviewed and non-peer reviewed surveys that attempted to measure student's attitude towards statistics and evaluated their construct and internal consistencies. They found four scales that have been widely used because of their robust psychometric properties: Statistics Attitude Scale (Roberts & Bilderback, 1980), Attitudes Toward Statistics Scale (Wise, 1985), the 28-item Survey of Attitudes Toward Statistics (Schau, Stevens, Dauphinee, & Del Vecchio, 1995), and the 36-item Survey of Attitudes Toward Statistics (Schau, Dauphinee, Del Vecchio, & Stevens, 2003). All of these scales contained at least 28 items. Researchers frequently use several variables or scales in their studies and it would benefit the research participants if they were not burdened with long questionnaires. This study dealt with creating abbreviated scales measuring students' attitude towards statistics. More recent studies have focused on measuring statistics anxiety and its impact on student learning (Chew & Dillon, 2014; Kohli, Peng, & Mittal, 2011; Williams, 2015) but this construct is not part of this investigation because student participants completed the survey instrument measuring attitudes towards statistics immediately

after they have registered for the course and have not been exposed to the details of statistical analyses and reasoning.

In online learning environments, learner autonomy has been hypothesized as a predictor of student achievement and satisfaction. Kerr, Rynearson, and Kerr (2006) found that independent learning, synonymous with learner autonomy, is an important characteristic in predicting online student success. According to Garrison (2003), online learning gives more control of the instruction to learners and past research in online distance education indicated that students need a high level of self-direction to succeed in online learning environments (Shapley, 2000; Song & Hill, 2007). Hawkins, Graham, Sudweeks, and Barbour (2013) suggested that affective rate, motivation level, and independent learning style are predictive of success in postsecondary online learning. Some studies characterized the successful distance student as an autonomous, independent learner (Kerr et al., 2006; Tucker, 2000), but Rovai (2003) found no correlation between learning style and learning outcomes. Varvel (2001) pointed out that successful online students tended to be self-disciplined and motivated with strong time-management skills; however, there has been no consensus on the impact of learner autonomy on student achievement in online learning environments.

The principal investigator teaches an introductory statistics course in an online independent study setting which has been plagued by low completion and low passing rates. To improve these measures of student achievement, she designed a randomized controlled experiment to investigate the impact of enhanced educational dialogue in the independent study course she teaches. One of the control variables in the study was learner autonomy. There are very few scales measuring this construct and the few in existence deals with language learning.

This study was designed to:

- develop new abbreviated, valid, and reliable scales of attitude towards statistics and learner autonomy;

- evaluate the new scales on an independent sample by assessing their factor structures, internal consistency, and model fit.

More specifically, this study aims to answer the following research questions pertaining to the new scales:

- Research question #1: To what degree does the observed factor structure correspond to the hypothesized factor structure?

- Research question #2: What is the estimated reliability of each of the scales of interest?

- Research question #3: What kind of hierarchical model best accounts for the correlations among the first-order factors as measured by confirmatory factor analysis?

Literature Review

This review begins with the process of scale development and the current recommendations for constructing valid scales. Then it evaluates current measures of attitudes towards statistics and learner autonomy, the most problematic of the measures of interest.

Scale Construction and Development

According to Clark and Watson (1995), the goal of scale development is to create a valid measure of an underlying construct and it is essential to begin with a clear conceptualization of the target construct by a review of the literature and consultation with experts. A thorough literature review is necessary to clarify the nature and range of the target construct, identify problems with existing scales, and justify the need for the proposed scale. Worthington and Whittaker (2006) echo this by recommending that the first step in scale development is to define the construct of interest clearly and concretely, guided by existing theory and practice. The next step would be to generate a pool of items that reflects the purpose of the target construct. The

content of this initial pool of items should be broad and over inclusive and careful attention should be paid to item wording. In addition, this initial pool should be reviewed by experts for content validity. The item pool should also be tested on a heterogeneous sample representing the entire range of the target population prior to factor analysis.

Nunnally (1978) suggested that having more scale points is better but there is a diminishing return after around 11 points. Having seven points tends to be a good balance between having enough points of discrimination without having to maintain too many response options. Sauro (2010) recommended that when designing a new scale, a 7-point response option will give a small benefit over a 5-point option and this benefit will only be gained for scales with fewer than 10 items and for very large sample sizes.

Although past research generally showed that including a neutral response will affect the distribution of responses and sometimes lead to different conclusions, Presser and Schuman (1980) found that, despite major shifts seen when including or excluding neutral options, the distribution of responses for the items did not change significantly. Bishop (1987) showed that different conclusions would be drawn about the proportion of respondents who favor or oppose an issue based on the inclusion of a neutral response. He concluded that the type of question and the type of opinion it elicits matter so one should carefully consider the context and the consequences of neutral opinions. Sauro (2011b) claimed that having a neutral point attracts respondents who actually slightly lean towards a favorable or unfavorable response and a neutral response masks these sentiments. An even number of options forces respondents to decide whether they think favorably or negatively toward an item. He also claimed that a neutral option does not matter much because items are summed, averaged, or combined and the effects of changing response options are usually modest.

There is also a tradition of including items with both positive and negative wording to minimize acquiescence and extreme response bias. However, there are a number of disadvantages to this tradition (Sauro, 2011a):

- Might result in respondents accidentally agreeing with negative items (mistakes)

- Might result in researchers forgetting to reverse the scales (miscoding)

- Lowers internal reliability – when researchers forget to reverse scales and coding, a negative Cronbach's alpha results

- Distorts factor structure – problems with misinterpreting negative items include creating an artificial two-factor structure for positive and negatively worded items.

- Increases interpretation problems with cross-cultural use

Sauro and Lewis (2011) conducted an experiment comparing a traditional questionnaire and an all positive version and they found little evidence of any differences in acquiescence or extreme response biases between the two versions. They also did not find any evidence for a strong acquiescence or extreme response bias in the all positive version of the questionnaire. They concluded that the problem of respondents making mistakes and researchers miscoding questionnaires is both real and much more detrimental than response biases. They recommended that researchers designing new questionnaires should avoid the inclusion of negative items.

Based on these studies, the new scale that was developed contains six scale points without a neutral category. Responses were formatted in a Likert scale with values ranging from 1 to 6 [1 (*strongly disagree)*, 2 (*disagree*), 3 (*somewhat disagree*), 4 (*somewhat agree*), 5 (*agree*), and 6 (*strongly agree*)]. Higher numbers described higher degrees of the attribute, for example, a score of 6 means a participant has a higher degree of learner autonomy or has greater

confidence in learning statistics. In addition, this new scale did not include items with positive and negative wordings, instead the items were all positively worded in a common direction.

Attitude Towards Statistics

The construct of attitudes has been defined as "not directly observable, inferred aspects, consisting of beliefs, feelings, and behavioral predispositions towards the object to which they are directed" (Auzmendi Escribano, 1992, p. 17). Past research has shown that "students with positive attitudes toward Statistics are likely to show strong academic performance in Statistics courses." (Nolan et al., 2012, p. 103). As a result, multiple instruments in the form of surveys measuring student's attitude toward statistics have been developed, starting as early as the 1950's (Bending & Hughes, 1954; Schau, Stevens, Dauphinee, & Del Vecchio, 1995; Van Hoof et al., 2011; Wise, 1985). According to Nolan et al. (2012)

> Although each of these surveys claims to measure student's attitude towards statistics, the dimensionality, items, and results vary among surveys, suggesting that this construct is not yet clearly defined. Currently, a summary and comparison of the validity and reliability evidence for these various interpretations is absent from the literature, making it difficult for statistics educators to make evidence-based decisions when selecting a survey or deciding where additional research and development are needed. (p. 103)

Their paper sought to identify all peer-reviewed and non-peer reviewed surveys that attempted to assess student's attitude towards statistics and evaluated their construct and internal consistencies. The authors looked at 532 citations from relevant electronic databases and reviewed 78 of the citations. From this review, 35 citations were included in the final analysis. Fifteen surveys were identified but only four scales had an accumulation of validity and reliability evidence. Table 1 compares these four scales.

Table 1

Comparison of Most Commonly Used Scales Measuring Attitude Toward Statistics

Scale	Number of Response Categories	Date Created	Number of Items	Number of and Dimensions Measured
Statistics Attitude Scale (SAS)	5-point	1980	34	One
Attitudes Toward Statistics Scale (ATS)	5-point	1985	29	Two (field and course)
Survey of Attitudes Toward Statistics (SATS-28)	7-point	1995	28	Four (Affect, Cognitive competence, Value, and Difficulty)
Survey of Attitudes Toward Statistics (SATS-36)	7-point	2003	36	Six (Affect, Cognitive competence, Value, Difficulty, Interest and Effort)

From the 15 surveys that were identified and evaluated by Nolan et al., three common elements emerged: (a) affect, (b) perceived ability to learn and/or understand statistics, and (c) perceived value of statistics. For future research, they recommended:

the need for additional, peer-reviewed validation research and improved consistency in reporting reliability evidence. Although four instruments were identified that had been used in multiple validation studies, none of the items and scores from the underlying dimensions had accumulated a large amount of content, substantive, structural or external validity, and none, specifically possessed evidence of all four. (Nolan et al., 2012, p. 120)

VanHoof et al. (2011) investigated the six-factor structure of SATS-36, the most widely used questionnaire, and concluded that it can be improved by removing some poorly functioning items and that either the six subscales could be used or three of them (Affect, Cognitive

Competence, and Difficulty) can be combined into one subscale without losing much information. They developed new abbreviated scales measuring perceived ability to learn statistics and the perceived usefulness of the field of study. Eight items were used to measure these two constructs.

Learner Autonomy

A preliminary search revealed that there is no single consensual definition of the term *autonomous learning* and its related constructs of *independent learning* and *self-directed learning* (Macaskill & Taylor, 2010; Thanasoulas, 2000). Moore (1993) posited in his theory of transactional distance that the psychological and communication distance between teacher and learner is influenced by three factors one of which is learner autonomy, the extent to which the learner controls the learning goals, experience, and assessment. Rovai (2003) claimed that "learner autonomy, that is, the concept of independence and self-direction, has been a hallmark of adult education and an assumed characteristic of the nontraditional students enrolled in distance education programs" (p. 12).

Murase (2007) believed that the operationalization of learner autonomy is a difficult task because it is widely considered to be multidimensional. It is also problematic and has not been applied to an online distance education statistics course. Holec (1981) described it as the ability to take charge of one's learning. A universal definition of autonomous learning or learner autonomy has not been agreed upon but the following characteristics are considered essential by Tassinari (2012):

- A metacapacity of the learners to take control of their learning process to different extents and in different ways according to the learning situation;

- A complex construct with the following essential components: cognitive and metacognitive, affective and motivational, action-oriented, and social; and

- A capacity of the learners to activate an interaction and balance among these components in different learning contexts and situations.

The most commonly used measure of learning autonomy is Guglielmino's Self-directed Learning Readiness Scale (1977) consisting of 58 items but questions have been raised about its construct validity (Fisher, King, & Tague, 2001; Straka & Hinz, 1996). Macaskill and Taylor (2010) offered an operational definition of learning autonomy as learners who can take responsibility for their own learning, are motivated to learn, gain enjoyment from their learning, are open-minded, manage their time well, plan effectively and plan tasks carefully, meet deadlines, are happy to work on their own, display perseverance when encountering difficulties, and are low in procrastination when it comes to their work. They developed a 12-item scale that was shown to be psychometrically sound but its predictive power has not been tested. This article does not test the predictive power of the scale that was developed but another study authored by the principal investigator includes learner autonomy as a predictor variable in an analysis of covariance with student achievement and satisfaction as response variables.

In this study, learner autonomy was defined as the extent in which the learner takes responsibility for their own learning as manifested by planning ones' own learning and being intrinsically motivated. Five items were used to measure this construct.

Need for this Research

In the realm of statistics education research, there is a need for short, valid, and reliable measures of attitude towards statistics. Specifically, two subscales which have been identified as essential: perceived ability to learn statistics and perceived value of statistics. These two

subscales have been hypothesized to be strong predictors of student success in introductory statistics courses. This research aims to fill this need.

In online learning environments, learner autonomy has been long considered an essential attribute of successful online learners but there has been a lack of short, valid, and reliable measures of this attribute. This research also aims to fill this gap. The goal is to provide future researchers with these three abbreviated scales to add to other hypothesized attributes of successful learners in online introductory statistics courses that need to be tested. These findings benefit both online students and their instructors as the latter design instruction and dialogue to engage their students in the course.

Method

Participants

The university's Institutional Review Board (IRB) approved this study in July 2013. A total of 1,062 students were enrolled in the independent study section of this introductory statistics course from August 2013 to February 2016. Of these, 63.7% were female and the average age was 27.40 years. The youngest student was 14 years old and the oldest student was 69 years old. Students had 12 months to complete the course with an option for a 3-month course extension. The average course duration was 32 weeks and details are shown in Table 2. The students were spread across the continental United States, Europe, and Asia. This statistics class satisfied the quantitative reasoning and advanced language requirements of general education in most colleges and universities. It consisted of 38 lessons with an online quiz associated with each lesson. Students were given three midterms and a comprehensive final exam. They were also asked to complete a pre-course survey immediately after registration.

Table 2

Characteristics of Participants

Variable	*n*	Min	Max	Mean	*SD*
Age	1062	14	69	27.40	9.172
High school GPA	216	2.13	4.00	3.45	0.766
Math ACT Score	223	14	35	24.20	4.862
Duration, in weeks	596	3	98	32.26	19.766

Instrumentation

The principal investigator developed a new self-report survey instrument derived from Schau et al.'s Survey of Attitudes Toward Statistics (1995) consisting of 28 items and Macaskill and Taylor's Learner Autonomy Scale (2010) consisting of 12 items. The online pre-course survey consisted of 13 items designed to measure the following constructs:

- Confidence in learning statistics

  o I feel confident in my ability to learn statistics.

  o I feel comfortable doing math story problems.

  o Statistics is not a difficult subject.

  o I have no desire to avoid stat courses.

- Opinion on usefulness of statistics

  o The study of statistics will be very useful in my daily life.

  o The study of statistics will be very useful in my work.

  o I am looking forward to learning statistics.

  o I will enjoy completing this online statistics course.

- Learner autonomy

  o I do very well learning on my own.

  o I can keep to a schedule.

    o   I plan to study well for this online statistics class.

    o   I will prepare well for each of the midterm exams.

    o   I don't need external rewards in order to feel motivated.

This questionnaire was piloted in spring term 2013 for 10 students enrolled in an on-campus statistics class and a group of six statistics teaching assistants for clarity of question wording. It was also reviewed by a psychometrician in the School of Education. These procedures established content validity of the new scales.

Data Analysis for Scale Development and Validation

After the data were collected from the independent study and department of statistics databases, they were merged and verified for accuracy. Afterwards, a two-phase analysis was conducted: exploratory factor analysis (EFA) using SPSS 25 and confirmatory factor analysis (CFA) using Mplus 8 (Muthén & Muthén, 1998).

The pre-course survey data were randomly divided into two parts: EFA was applied to one half of the data and CFA was used on the other half. This was done to determine if the measurement model was reproduced in these two independent samples. Content validity of the questions was sought and established by a pilot study and review by a psychometrician. Once the best-fitting measurement model was identified, the scales were constructed using structural equation modeling (SEM) in Mplus.

For the EFA phase, the Principal Axis Factoring extraction and Promax oblique rotation methods were used as recommended by Worthington and Whittaker (2006). The following criteria were applied to determine which factors to retain: factors with more than two items, Scree test, and parallel analysis. The following criteria were used to determine which items to delete: items with factor loadings less than .30 (Brown, 2014; Kim & Mueller, 1978) or cross-

loadings with less than .15 difference from an item's highest factor loading (Worthington & Whittaker, 2006). For the CFA phase, the following fit indices were used to identify the model with the best overall fit: (a) the chi-square goodness of fit test with corresponding degrees of freedom and *p*-value, (b) the root mean square error of approximation (RMSEA) with corresponding 90% confidence intervals, (c) the confirmatory fit index (CFI), (d) the Tucker-Lewis Index (TLI), and (e) the standardized root mean square residual (SRMR) (Worthington & Whittaker, 2006). The acceptable fit criteria proposed by Wang and Wang (2012) were also used: both CFI and TLI should be greater than 0.90, both RMSEA and SRMR should be less than 0.08, and the upper limit of RMSEA's 90% confidence interval (CI) should be less than 0.08.

<center>**Findings**</center>

Research Question #1: Degree the Observed Factor Structure Corresponds to the Hypothesized Factor Structure

The half of the data used for EFA had *n* = 504. The initial analysis of the 13 items using Principal Axis Factoring and Promax oblique rotation methods extracted three factors which explained 52.02% of the common variance and with a Kaiser-Meyer-Olkin (KMO) sampling adequacy measure of .818 which is in the good range (Worthington & Whittaker, 2006). The resulting pattern matrix had two cross-loading items which were dropped from the model. These items were: *I have no desire to avoid Stat courses* and *I can keep to a schedule*. After these two items were excluded, the resulting EFA model had 11 items and three factors which explained 54.72% of the common variance with a KMO measure .794. The correlations among the three factors ranged from .259 to .549. These relatively low values of the factor correlations indicate discriminant validity and show that these three factors were measuring different constructs.

Parallel analysis was used in conjunction with a scree plot analysis to determine the number of factors to extract. According to Cho, Li, and Bandalos (2009), parallel analysis performs reasonably well in situations where data are dichotomous or ordinal. A scree plot and a parallel analysis confirmed the 3-factor model which are shown in Figure 1 and Table 3. In parallel analysis, eigenvalues from the sample correlation matrix are compared with the 95th percentile values from the analysis. If the eigenvalue of a factor is greater than the 95th percentile eigenvalues derived from the parallel analysis, then the factor is retained.

Note, however, that an item that was meant to measure learner autonomy (i.e., I do very well learning on my own) loaded highly on confidence in learning statistics. And another item meant to measure learner autonomy (I can keep to a schedule) cross loaded on confidence in learning statistics and was dropped from the analysis. As a result, only three items were retained to measure learner autonomy instead of the original five.

Table 3

Parallel Analysis with 11 Items

Eigenvalues for Sample Correlation Matrix	95th Percentile Eigenvalues from Parallel Analysis
3.893	1.304
1.841	1.233
1.399	1.174
0.861	1.110

Source: SPSS 25
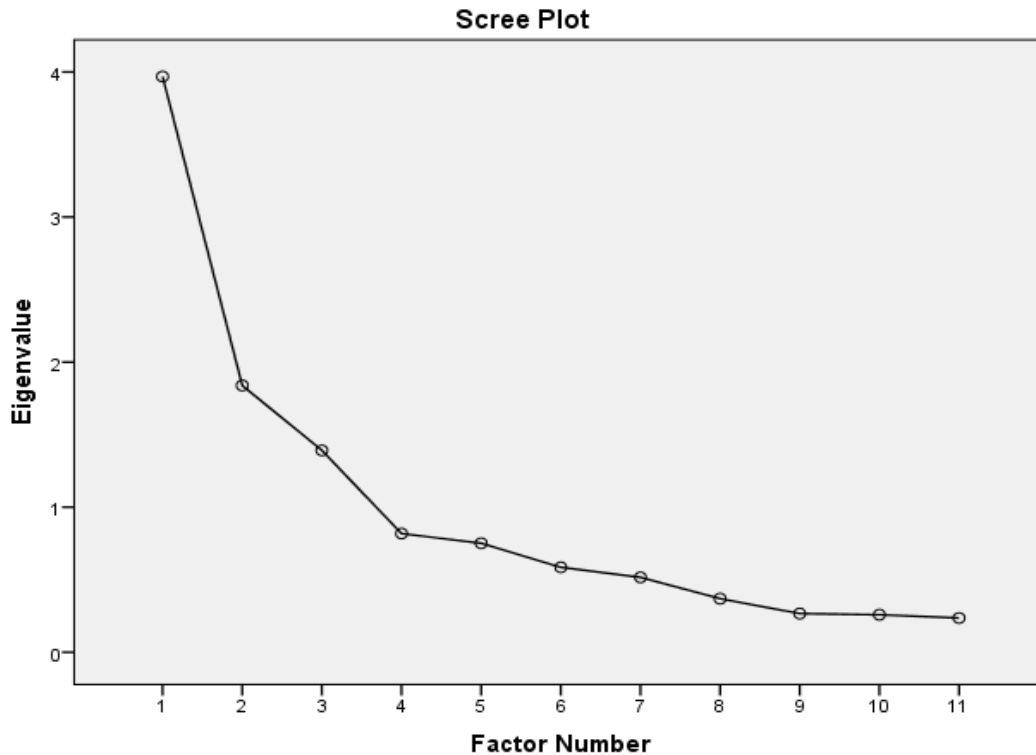
Figure 1. Scree plot for 11 items.

Research Question #2: Estimated Reliability of Each of the Scales of Interest

To assess the reliability of the three extracted factors, Raykov's rho was calculated for each one of the factors. An item pair within the usefulness of statistics construct had a non-negligible error covariance and another item pair within the learner autonomy construct also had a non-negligible error covariance. Because of the presence of these error covariances, Raykov's rho was used as a more appropriate reliability coefficient (Raykov, 2009). The rho estimates for the three factors were all in the good range: Factor1 Usefulness of statistis (.8351), Factor 2 Confidence in learning statistics (.8267), and Factor 3 Learner autonomy (.8987). The three extracted factors with their labels, items comprising the factors, and item pattern matrix loadings are shown in Table 4.

Table 4

Factor Loadings for EFA Using Principal Axis Factoring and Promax Oblique

Rotation Factor	Item Number	Statement	Factor Loadings
1	1	The study of Statistics will be very useful in my daily life.	.916
	2	The study of Statistics will be very useful in my work.	.868
	3	I am looking forward to learning Statistics.	.703
	4	I will enjoy completing this online Statistics course.	.411
2	1	I feel comfortable doing Math problems.	.776
	2	I feel confident in my ability to learn Statistics.	.719
	3	I do very well learning on my own	.651
	4	Statistics is not a difficult subject.	.565
3	1	I plan to study well for this online Statistics class.	.902
	2	I will prepare well for each of the midterm exams.	.798
	3	I don't need external rewards in order to feel motivated.	.320

Research Question #3: Hierarchical Model that Best Accounts for the Correlations Among the First-order Factors as Measured by CFA

The other half of the data used for CFA had $n = 503$. The EFA 3-factor model with 11 items was the initial model used for CFA. The fit statistics for this initial model were in the not-so-good range and areas of poor fit were identified by examining the modification and model fit indices. The largest modification index indicated that the model incorrectly identified two measurement errors as uncorrelated. The resulting CFA model had better fit statistics but a large modification index was still present: one more pair of items had correlated errors. After the appropriate error covariances were added to the model, all the fit indices improved as shown in Table 5. In addition, a chi-square test of model fit was run to formally test the difference between the three CFA models in Mplus. The adjusted chi-square values as recommended by Muthén and Muthén (1998) are shown in Table 5. These values indicate that the model is a good

fit for the data (Wang & Wang, 2012). See also Figure 2 for the path diagram of this third best

fitting CFA model.

Table 5

Comparison of Fit for Three CFA Models

Model	Number of Correlated Error Pairs	CFI	TLI	RMSEA	SRMR	Model Fit χ^2-test statistics	p-value for $\Delta \chi^2$
1	none	.900	.866	.085	.071	238.550	
2	1	.951	.933	.060	.063	142.419	.0000
3	2	.962	.947	.054	.051	118.505	.0000
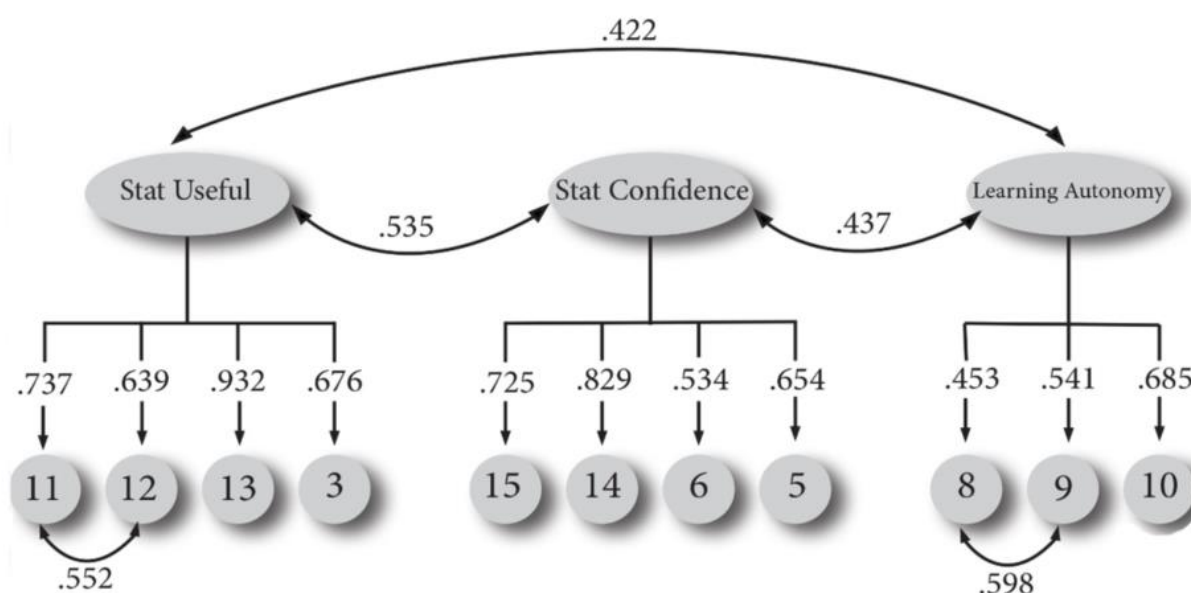
Figure 2. Path diagram for the three-factor structure and factor correlations.

The low factor correlations shown in Figure 2, which ranges from .422 to .535, also support the

discriminant validity of these three factors. Based on these EFA and CFA results, we can

conclude that these three extracted factors comprise abbreviated, reliable, and valid measures of

opinion on Usefulness of statistics, Confidence in learning statistics, and Learner autonomy.

Discussion and Implications

Discussion

There is a need for short, valid, and reliable scales measuring attitude towards statistics and learner autonomy in statistics education and online learning research. The aim of this study was to fill this need by constructing such scales. The new scales that were developed were validated using two independent samples of students. They went through content validity inspection and showed that they were adequate measures of the constructs of interest because they explained 54.72% of the common variance and had a KMO sampling adequacy measure of 0.794. They have construct validity because all items loaded highly on the three extracted factors and the average loading per factor were all greater than .67. The final SPSS pattern matrix had no cross loadings and all factor correlations had absolute values less than .60 which show discriminant validity. Finally, these three factors demonstrated that they were reliable measures because their Raykov's rho values were all in the good range (.8267 to .8987).

Confirmatory factor analysis validated the three-factor structure of the survey instrument. Using the cut-off recommendations for good model fit based on Yu (2002) and Marsh, Hau, and Wen (2004), this measurement model is adequate. The EFA and CFA results show that these new scales provide a valid, adequate, and reliable instrument for measuring perceived usefulness of statistics and confidence in learning statistics. The sound psychometric properties of these abbreviated measures suggest that they are suitable for inclusion in new research projects in the realms of statistics education and online learning.

This study also demonstrated the adequacy of using one-directional items with no mix of positive and negative items and using six-point Likert-type scales. However, further studies are

needed to examine the predictive validity of these abbreviated measures in different learning environments.

These new scales can be confidently used in statistics education, online learning, and blended learning research. For future studies, it might also be useful to investigate independent learning processes and attributes of autonomous learners in different contexts to improve the conceptualization and operationalization of learner autonomy. Further, a better measure of learner autonomy should be obtained by adding more affective items like *I'm happy studying on my own* or *I enjoy finding information on my own*. The time management items could be improved by being more school-learning-environment-specific like *I try to schedule adequate time to study for each of my classes* or *I can keep to a schedule of study*.

Implications

This study supports claims for not including a mix of positive and negative items in valid scale development. In addition, having six response options and at least three items to measure a construct seems to be adequate based on the EFA and CFA results. Researchers using these abbreviated scales will have measures that compare favorably with longer existing scales. The findings in this study may then facilitate scale development.

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Article #2: Enhancing Educational Dialogue to Promote Student Success in an Online

Independent Study Statistics Course

Enhancing Educational Dialogue to Promote Student Success

in an Online Independent Study Statistics Course

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Abstract

This study examined the impact of enhanced educational dialogue in terms of email feedback on course progress and an invitation to participate in a discussion board on student achievement and course satisfaction in an introductory statistics course offered in an independent study setting. Participants in the study were randomly assigned to different types and levels of educational dialogue and their completion status, final exam scores, average quiz scores, and course satisfaction ratings were compared after controlling for these covariates of interest: age, gender, high school GPA, Math ACT score, learner autonomy, opinion about usefulness of statistics, and confidence in learning statistics. The different types and levels of educational dialogue used in this study were: email reminders only, discussion board invitations only, email reminders and discussion board invitations, and no email reminders nor discussion board invitations.

The MANCOVA results show that students who have higher confidence in learning statistics have significantly higher final exam scores and higher course satisfaction ratings. The findings also show that students assigned to the email group have the highest average quiz scores. The logistic regression results show that older students and those who have high confidence in learning statistics are more likely to complete the course. Overall, the completion rate for this study was significantly higher than the previous sections of the course.

Keywords: online learning, instructional dialogue, attitude towards statistics, learner autonomy, student performance, course satisfaction

Enhancing Educational Dialogue to Promote Student Success in an Online

Independent Study Statistics Course

Since their inception, distance education and online courses have been plagued with low completion and passing rates which have negatively impacted the students and institutions which offer these courses. Ali and Leeds (2009) claimed that completion rates are at least 20% lower in online courses than in traditional face-to-face courses. For example, out of 1,255 students enrolled at an introductory statistics course in an online independent study course from 2011-2012, 51% completed the course, 29% let their course expire after 12-15 months (students can request a three-month extension for a minimal fee), and 20% officially withdrew from the course. Of those who completed the course, 18% obtained a grade of D+ or lower. Numerous studies have attempted to determine the causes of these high dropout rates and low passing rates but these studies involved on-campus, non-self-paced online courses or online orientation courses for new hires in corporate settings (Diaz, 2002; Frankola, 2001; Parker, 2003). This research involves an off-campus, self-paced online independent study course available to undergraduate students for 12-15 months.

Past studies administered surveys to current students or past students in online distance education who did not complete the course to determine why they dropped out (Angelino, Williams, & Natvig, 2007; Diaz, 2002; Nash, 2005; Parker & Greenlee, 1997). These studies mentioned the importance of student's motivation, technical training, academic self-concept, reading skills, and study skills as predictors of success in distance education. Parker and Greenlee (1997) reported that the most important factors for non-completion were financial problems, family complications, work schedule conflicts, and poor academic performance. Some of these factors are beyond the control of instructors and institutions of learning. Some studies proposed course improvements or interventions but did not empirically test their

proposed solutions (Aragon, 2003; Garrison & Cleveland-Innes, 2005; Lemak, Shin, Reed, & Montgomery, 2005). A few empirical studies sought to validate their suggested solutions but focused on single variables which can give misleading or fruitless results (Nash, 2005; Swan, 2001; Wheeler, 2007). Drop-out rates are influenced by many variables which may affect each other and single variable studies do not allow for possible interactions among these variables of interest (Ali & Leeds, 2009; Nash, 2005). This study used a multivariate model to find valid and reliable predictors of student success, defined as student persistence, student performance, and student satisfaction, in an online distance education setting (Gibson, 1991; Shin, 2003).

Furthermore, most of the studies conducted to validate suggested interventions used non-probabilistic sampling methods or quasi-experimental designs (Leeds et al., 2013; Lemak, Shin, Reed, & Montgomery, 2005; Lim, Morris, & Yoon, 2006). Thurmond and Wambach (2004) pointed out that "the bulk of research in distance education has not used a true experimental design, which allows researchers to make stronger causal inferences. The majority of the studies reviewed used a descriptive, exploratory design conducted in the natural setting" (p. 20). No randomized, controlled, and double-blinded experiments that tested the effectiveness of previously suggested course improvements were found. This research aimed to fill this gap. The independent study context of this study provided a unique opportunity to conduct a randomized controlled experiment because students could be randomly assigned to treatment groups once they enroll in the course.

Distance education courses that have higher completion rates, higher student achievement, and higher student satisfaction are those with higher levels of teacher-student interaction or dialogue (Roblyer, 2008; Roblyer & Marshall, 2003). The chosen interventions in this study to increase educational dialogue were twice-a-month email reminders to students

lagging behind or performing poorly in course work, and an invitation to participate in a statistics-related discussion board where topics are posted for teacher-student and possible student-student interaction after certain lessons have been completed. The research question is *What is the impact of enhanced educational dialogue in an introductory statistics course for undergraduate students on completion rates, student achievement, and course satisfaction in an online independent study course after controlling for age, gender, previous academic achievement, learner autonomy and attitude towards statistics?*

Literature Review

Theories in Online Distance Education

Distance education practitioners and researchers have always been concerned with low completion rates, low student achievement, and low course satisfaction. These concerns stemmed mainly from the existence of geographical distance in distance education courses which resulted in delayed assessment feedback and lack of teacher-to-student interaction and personal connection. To address these concerns, several theorists proposed theoretical frameworks underpinning success in online distance education. Three theories relevant to this research study are: Moore's theory of transactional distance, Garrison's community of inquiry model, and Anderson's theory of online learning interactions.

Theory of transactional distance. Michael Moore (1993) posited the theory of transactional distance which defined transactional distance as "a psychological and communications space to be crossed, a space of potential misunderstanding between the inputs of the instructor and those of the learner" (p. 22). This space can occur in both traditional and distance education instruction. The theory claims that "distance is not simply a geographic separation of learners but is a pedagogical concept" (p. 22) which describes all possible

relationships between teacher and learners when they are separated by space and/or time. Moore identified three variables that affect transactional distance between learners and teachers: instructional dialogue, course structure, and learner autonomy. He defined instructional dialogue as a positive interaction between teacher and learner that leads to improved student understanding. He also noted that a form of dialogue occurs even in courses that have no interaction, such as when the student is given printed materials, audiotapes or videotapes.

Dialogue is also influenced by content and class size. For example, science and mathematics courses use a more teacher-directed approach having less dialogue. Group size also determines the amount and extent of interpersonal dialogue that may occur in any instructional system (Gorsky, Caspi, & Smidt, 2007). Large classes, consisting of more than a thousand students, will have a minimal amount of teacher-student interaction.

Moore defined course structure as the flexibility of the curriculum's learning objectives and evaluation methods, and learner autonomy as the extent to which the student controls the learning experiences and course assessment. He theorized that if instructional dialogue increased and course structure and learner autonomy decreased then transactional distance will decrease.

Lemak et al. (2005) conducted an empirical investigation regarding technology, transactional distance, and instructor effectiveness. They analyzed instructor-evaluation data from 406 distance learning students in the U.S. and concluded that transactional distance affected perceived teacher effectiveness. Moore (2003) and Aragon (2003) claimed that increasing instructional dialogue and teaching presence in distance education will decrease transactional distance and improve student performance and satisfaction. Gorsky and Caspi (2005b) reviewed several studies attempting to support or validate Moore's theoretical model through empirical research. They found that either the findings partially supported the theory or those that

supported the theory lacked reliability and or construct validity. They also claimed that the theory may be reduced to a single proposition, "as the amount of dialogue increases, transactional distance decreases" (p. 1). Giossos, Koutsouba, Lionarakis, and Skavantzos (2009) also reviewed existing studies relating to Moore's theory and found a variety of functional definitions of transactional distance that revealed an absence of consensus. They proposed defining transactional distance as the distance in understanding between teacher and learner. The proposed study focuses on examining different types and levels of instructional dialogue applicable in large online distance education, while controlling for learner autonomy, to improve student performance. The concepts of transactional distance and course structure are not addressed in this study.

Community of inquiry theory. Garrison, Anderson, and Archer (2003) sought to provide a theoretical framework to explain online distance education practice in the context of computer mediated communication (e.g., computer conferencing) to create a community of learners at a distance. They identified three overlapping elements (teaching presence, social presence, and cognitive presence) of a community of inquiry to create deep and meaningful learning experiences. This paper focus on the teaching and social elements because they are the only aspects, in the context of this study, that can be manipulated (unlike cognitive presence). Garrison, Clevelan-Innes, and Fung (2010) defined teaching presence as the design, facilitation and direction of cognitive and social processes for the purpose of realizing personally meaningful and educationally worth-while learning outcomes" (p. 32). Teaching presence should diagnose the needs and provide timely information and direction to the learner–these are some of the goals of the bi-monthly email reminders. Social presence is defined as the "ability of participants to identify with the course of study and communicate purposefully in a trusting

environment, and develop inter-personal relationships" (p.32). Because this study is an independent study course where students are in different stages of progress in the course, developing inter-personal relationships among the students is not the goal of the chosen interventions. However, the discussion board invitation is an attempt to help students identify with the course of study.

Aragon (2003) emphasized that social presence is one of the most significant factors in improving instructional effectiveness and building a sense of community. Social presence has been shown to affect cognitive presence positively but online social presence does not happen automatically, it has to be structured. Teaching presence can help structure social presence by defining and initiating discussion topics and by focusing the discussion. Garrison and Cleveland-Innes (2005) concluded that "teaching presence in the form of facilitation is crucial in the success of online learning" (p. 136). It may be possible, even in relatively large classes, to structure some social presence between students and teaching assistants who can initiate and respond to student postings.

Rourke, Anderson, Garrison, & Archer (2007) provided a community of inquiry model for online learning environments using Garrison's three presence components: cognitive, social, and teaching. Picciano (2002) noted that Rourke et al. advised research on each of these individual components and argued that "What is critical here is that presence in an online course is fundamentally a social phenomenon and manifests itself through interactions among students and instructors" (p. 24). Wallace (2003) further pointed out that the "consensus in studies of online community is that community can be developed in online learning environments, and that it plays an important role in student success …. however, the literature is more anecdotal and case-based" (p. 269) and no research has probed whether the existence of community is related

to student learning outcomes. The proposed study attempts to link teaching presence and social presence as components of the community of inquiry to student learning outcomes.

Theory of online learning interactions. Anderson (2003) proposed a theory of online learning interactions where he claimed that the role of interaction is a crucial element of the education process. He quoted Daniel and Marquis' seminal article in 1979 challenging distance education educators to "get the mixture right between independent study and interactive learning" (p. 1). He used Wagner's definition of interaction as "reciprocal events that require at least two objects and two actions. Interactions occur when these objects and events mutually influence one another" (p. 11). He also expounded on the nature and importance of six forms of educational interactions: student-student, student-teacher, student-content, teacher-teacher, teacher-content, and content-content. He further pointed out that interaction within a community of inquiry binds learners in time and are generally more expensive and challenging to scale to a large number of students.

In summary, various distance education theories have emphasized the importance of student-teacher interaction for success in online distance education courses. However, as defined by these theories, interaction is a mutual two-way communication between students and teachers or teaching assistants. In large online distance education courses, a positive two-way interaction or dialogue may not be possible and pseudo-interaction in terms of automated email messages based on student performance and periodic invitations to participate in a discussion board initiated and facilitated by teaching assistants may be enough to provide a sense of belonging and community that might impact student performance and course satisfaction.

Research Behind Chosen Interventions

Gorsky, Caspi, and Smidt (2007) conducted a study regarding the use of instructional dialogue in a distance education physics course and found that a large majority of students turned to their instructors for assistance and not to their fellow students. This research focus on teacher-student dialogue as manifested by email messages (feedback on course activity and quiz performance, reminders, compliments for job well done, encouraging messages, and targeted advise to achieve higher performance) and invitations to participate in an online discussion board.

Gorsky and Caspi (2005a) and Caspi and Gorsky (2006) in their unified theory of instruction laid out two propositions: "first, every element in an instructional system is either a dialogue or a resource which supports dialogue, and second, dialogues and learning outcomes are correlated" (2006, p. 736). In this study, emails are treated as a resource which supports dialogue. The second proposition laid out by Gorsky and Caspi (2005a) is that dialogue is correlated with learning outcomes, specifically, student achievement and satisfaction. There is considerable literature regarding the relation between teaching presence and perceived learning and student performance. Hay, Hodgkinson, Peltier, and Drago (2004) showed that instructor-student interaction was stronger than student-student interaction in terms of predicting effectiveness for both online and traditional courses. Swan (2001) also found that "interaction with instructors seemed to have a much larger effect on satisfaction and perceived learning than interaction with peers" (p. 322).

Anderson (2004) referenced Bransford, Brown, and Cocking's (1999) four overlapping aspects of learning environments: learner centered, assessment centered, knowledge centered, and community centered. He suggested that "learner-centered activities make extensive use of

diagnostic tools and activities, so that these pre-existing knowledge structures are made visible to both the teacher and the student" (p. 35) and to use "strategies that are designed to provide formative and summative assessment with minimal direct impact on teacher workload" (p. 38). In this course, the 38 quizzes associated with the 38 lessons provide formative assessment and email feedback on student achievement (quiz completion and score) every two weeks acts as a diagnostic tool that might be beneficial to students.

Fredericksen, Pickett, Shea, Pelz, and Swan (2000) reported that the most significant explanatory variable for learning in an online course was students' interaction with the teacher. In their review of the literature regarding interactions in distance education, Thurmond and Wambach (2004) reported several multiple stepwise regression results which indicated that learner-instructor interaction was the most significant predictor of perceived learning. Wheeler (2007) found that email facilitated the highest level of immediacy of dialogue for most students and that the effects of transactional distance could be better analyzed if two sub-variables of dialogue are recognized: social presence (the perception of connectedness between students and their teachers or tutors) and immediacy (the temporal effects of dialogue). However, he did not relate reduced transactional distance specifically to increased student performance or satisfaction.

Frankola (2001) listed three reasons why online learners drop out in corporate settings: lack of management oversight, lack of motivation, and lack of student support. His proposed solutions to decrease dropout rates that are relevant to this research project are given: (a) create discussion groups; (b) use software to track student progress and email non-participating students or potential course dropouts; (c) provide access to tutors through email, phone or threaded discussions; and (d) provide an online database for answers to most frequently asked questions.

Aragon (2003) suggested the following strategies for creating social presence within social environments: (a) develop a welcome video, (b) contribute to discussion boards, (c) promptly answer emails, (d) provide frequent feedback, and (e) use humor and emoticons. Lemak et al. (2005) and Lehman, Kauffman, White, Horn, and Bruning (2001) also found that the use of email enhanced the educational experience. Simpson (2003) pointed out the positive influence of offering encouragement through a telephone call, postcard or email. In some studies cited in Simpson (2003), such contact did not even need to be personalized to be successful, though Simpson suggested that such contacts be brief, informal, and appropriate. Having such contact across the period of study was also found beneficial for retention. Roblyer (2006) found that policies and practices that required teachers to track student progress and proactively reach out to inactive students via emails as best practices. However, these policies and practices were not based on formal research and were not linked to improved academic performance. Hawkins, Graham, Sudweeks, and Barbour (2013) recommended that teachers take proactive measures to reach out to students regardless of their progress in the course. The increased interaction may be enough to move students from the non-completion status to completion status.

In this study, participation in discussion boards is not required or graded but encouraged with the information that discussion board topics are associated with the essay portion of the exams and writing assignments. Picciano (2002) warned that

> While much of the research relates student satisfaction and performance to the active participation in online course activities, faculty teaching these courses face a small dilemma in establishing requirements for interacting online because some students may not need to participate actively in the course to do well on a test or some other performance measure. (p. 23)

The nature of the course also precludes in-time discussion because students are in different stages of course completion. However, the regular monitoring of student responses by teaching assistants might enhance student-teacher dialogue.

Other Predictors of Online Student Success

Diaz (2002) listed eight factors that influence dropout rates: demographics, quality of class, discipline, educational preparation, motivational and persistence attributes, socio-economic factors, teacher experience, and online orientation process. Lack of personal interaction with teachers and peers was also given as one of the main reasons for low completion rates. Aragon and Johnson (2008) investigated the factors that influence completion rates in community college online courses. They found that previous GPA, as measured at entry at the beginning of the semester of data collection, was significantly different for completers and non-completers in online courses. Students with lower GPAs were more likely to drop their online courses (Dupin-Bryan, 2004; Hawkins, 2013; Parker, 2003; Roblyer, Davis, Mills, Marshall, & Pape, 2008). Accordingly, high school GPA was used as a covariate of interest in this study.

Hawkins (2013) discussed several factors that might influence student performance in postsecondary online learning. Among them were gender, age, prior academic success, motivation level, and independent learning styles. Bean and Metzner (1985) also identified four factors that affect persistence. One of them was background and defining variables such as age, educational goals, ethnicity, and prior GPA. Ross and Powell (1990) reported that females tend to be more successful in online courses than males. Rovai (2001) found similar gender-related differences in an online course. Hence, gender and Math ACT score as a measure of academic background and Math aptitude were added as covariates.

Tucker (2000) characterized successful distance students as autonomous, independent learners. There is no formal consensus on the definition of learner autonomy. Moore (1993) defined learner autonomy in terms of learners being able to determine learning goals and assessment methods. He theorized that learners with high autonomy prefer less dialogue and less structure. Learners with low autonomy will depend more on the teacher and favor more dialogue and more structure. In this study, the only aspects of the course that learners can control are the time, place and, pace of study. As such, Moore's definition will be restated in terms of independent learning or self-directed learning where students take responsibility for their learning.

The most common measure of learner autonomy is Guglielmino's Self-Directed Learning Readiness Scale (SDLRS, 1977) which consists of 58 items. This scale has been the subject of various construct validation studies which recommended its discontinuance (Candy, 1991; Field, 1989; Straka & Hinz, 1996). Doherty (2000) and Pachnowski and Jurczyk (2000) used SDLRS and both studies found that self-directedness was not a strong indicator of academic success in an online course. In 2010, Macaskill and Taylor developed a measure of learner autonomy with better psychometric properties than SDLRS and which consisted of 12 items. The principal author in this study developed a 3-item measure of learner autonomy which was defined as the extent in which the learner takes responsibility for planning their own learning and being intrinsically motivated. This abbreviated measure has adequate and sound psychometric properties: its reliability estimate using Raykov's rho is .8987 and the factor loadings of the three items ranges from .320 to .902 as shown in Table 6 and is used as another covariate in the study.

Table 6

Factor Loadings for EFA Using Principal Axis Factoring and Promax Oblique Rotation for Learner Autonomy

Items	Factor Loadings
I plan to study well for this online Statistics class.	.902
I will prepare well for each of the midterm exams.	.798
I don't need external rewards in order to feel motivated.	.320

Source: SPSS version 25.

In statistics education research, previous studies have shown that attitude towards statistics is one of the biggest predictors of achievement in research methodology and statistics courses (Finney & Schraw, 2003; Garfield & Ben-Zvi, 2007; Onwuegbuzie & Wilson, 2003). The Survey of Attitudes Toward Statistics (SATS-36) developed by Schau (2003) has been found to be a valid and reliable instrument by the Statistics education community. However, it consists of 36 items and is only available for a fee. The principal investigator developed and validated abbreviated scales measuring perceived usefulness of statistics and confidence in learning statistics, which were deemed to be the more important subscales of SATS-36 (Nolan, Beran, & Hecker, 2012; Van Hoof, Kuppens, Sotos, Verschaffel, & Onghena, 2011). The estimated reliability estimates of these scales using Raykov's rho are .8351 for Perceived usefulness of statistics and .8267 for Confidence in learning statistics, which are within the range of good internal consistency (Raykov, 2009). These two scales also have construct validity because their factor loadings range from .411 to .916 for Perceived usefulness of statistics and from .565 to .776 for Confidence in learning statistics (Brown, 2006; Kim & Mueller, 1978), see Table 7.

In summary, numerous studies have focused on the factors that affect student persistence, student achievement, and student satisfaction in online distance education. Using Moore's

transactional distance theory, Garrison's community of inquiry model, and Andersons' theory of online learning interaction, these studies have shown the importance of teacher-student dialogue in reducing transactional distance which in turn leads to greater student performance and student satisfaction. Some of these studies have proposed specific interventions to increase teacher-student interaction. While many possible solutions have been proposed, few have been tested empirically. The few evidence-based studies showed mixed results and were not in complete agreement. This research project used some of the proposed solutions that were controllable and achievable. Specifically, this research aimed to enhance instructional dialogue by the use of regular email feedback on student progress and reminders to students who are lagging behind in course work and the use of statistics-related discussion boards monitored and responded to by tutors. To account for other variables that may affect the outcome of the study, age, gender, previous student achievement, level of learner autonomy, and attitude toward statistics were used as control variables.

Table 7

Factor Loadings for EFA Using Principal Axis Factoring and Promax Oblique rotation for Attitude Towards statistics

Factor	Item Number	Statement	Factor Loadings
Usefulness	1	The study of Statistics will be very useful in my daily life.	.916
	2	The study of Statistics will be very useful in my work.	.868
	3	I am looking forward to learning Statistics.	.703
	4	I will enjoy completing this online Statistics course.	.411
Confidence	1	I feel comfortable doing Math problems.	.776
	2	I feel confident in my ability to learn Statistics.	.719
	3	I do very well learning on my own	.651
	4	Statistics is not a difficult subject.	.565

Source: SPSS version 25

Method

Participants

A large private university in the western United States offers an online introductory statistics course through its Independent Study program. This course satisfies a couple of general education requirements for most colleges and universities with college algebra as a prerequisite. Students, nationwide and worldwide, can enroll in the 12-month online course anytime with an option to extend the course for three months. They proceed at their own pace with no interaction with their fellow students. The course is taught and managed by a full-time faculty member from the school's department of statistics. It is highly structured with the same learning objectives, course materials, quizzes, and exams as the on-campus course. It consists of 38 lessons and 38 quizzes associated with each lesson. It has three midterm exams and a comprehensive final exam. These quizzes and exams are reviewed twice a year by a committee consisting of at least four faculty members teaching the on-campus course. Questions are chosen for clarity and alignment with the lesson and course learning outcomes.

This online course has a very low teacher-student interaction because the school's Independent Study office shields the instructor from student questions and requests. There is, however, a help desk that is available seven days a week, 24 hours a day that students can call, toll free. Students can also call or email undergraduate teaching assistants, called Stat tutors, from 10:00 a.m. to 6:00 p.m. MDT, Monday to Friday.

The participants in this research project were all the Independent Study students enrolled in the introductory statistics course from August 2013 to February 2016. It was not the intent of the study to generalize the findings to the population so random selection of participants was not planned. The intent was to establish a cause-and-effect relationship between enhanced

instructional dialogue and student success in online learning so random assignment of the participants to different levels of student-teacher dialogue was the essential element.

Details of Chosen Interventions

The school's Institutional Review Board (IRB) approved the study in July 2013. Students who did not consent to participate in the study were enrolled in the non-participant group which consisted of the previous course offered in 2012, with the addition of a welcome video and a list of frequently asked questions. The students who consented to participate were randomly assigned to a course similar to the non-participant group with the addition of the following types and levels of educational dialogue:

- Control group, the same as the non-participant group.

- Email group, the control group with timely email reminders of course progress and encouragement. Three email templates were sent out depending on student performance (see Appendix B).

- Discussion Board group, the control group with a Statistics-related discussion board monitored and responded to by Stat tutors on a weekly basis. After students were assigned to the Discussion Board group, they were sent an email inviting them to join the discussion board by responding to questions that were periodically emailed to them. The first email was sent two months after the course was made available for registration to make sure enough students have completed lesson 3. Every month thereafter, an email was sent for each of the nine discussion board questions (see Appendix C). After the first year, all questions were resent in monthly emails. Students could choose to click on the email link to view the posted questions and after viewing, students could choose to respond to the questions. In the discussion board group, there were three levels of

exposure chosen by the subjects: no view, view only, and responded. Participation in discussion boards was not required and was not graded. This decision was made because some students may not need to participate in the discussion to do well on the quizzes and exams (Picciano, 2002).

- Email and Discussion Board group, the control group with timely email reminders of course progress and a statistics-related discussion board monitored and responded to by Stat tutors on a weekly basis.

The email group was sent reminders on the 15th and 29th day of the month from the course website. This email was automated and signed by the team of instructor and Stat tutors. Congratulatory emails were sent to students who completed three quizzes in a week, from Sunday to Sunday, or who obtained at least 85% on the last three attempted credit quizzes. Encouraging emails were sent to students who had not completed any quizzes and had not accessed the course website for two weeks or who obtained a credit quiz average less than 65% on the last three attempted quizzes. The email scripts are found in Appendix B.

The discussion board group members were sent an email immediately after they registered on the course website inviting them to post comments and respond to posted comments of their fellow students and the Stat tutors after they have completed certain lessons. It was hinted that these discussion questions might help students in the essay portion of the exams and the writing assignments. Some examples of discussion questions were *In data collection, why is random selection important in observational studies? Why is random assignment of subjects to treatments critical in controlled experiments? Why does association not imply causation? Explain and give examples.*

All students were informed of the study protocol, including potential risk of participation and the amount of extra course assignments they may be asked to complete. They were also informed of the purpose of the study and its potential benefit to their learning. The different types of educational dialogue were not explicitly described so participants could be blinded to the type of dialogue they were assigned to. Before starting the course, all enrolled students were asked to complete a questionnaire measuring learner autonomy and attitude toward statistics. For those who completed the course, a course satisfaction survey was given as their last quiz. For those who withdrew or let the course expire, a short survey was given asking for their reason or reasons for dropping out.

Operationalization of the Variables of Interest

The explanatory variable was the type of educational dialogue a participant was randomly assigned to, as described in the previous section. The outcome variables were measures of student performance and course satisfaction. These were the following:

- Completion status. Students who completed the course are those who obtained a grade (A, B, C, D or E) in the course. If students retake the course, the most recent attempt was defined as the one where they completed the Final exam and obtained a grade for the course that is not a W for withdrawn.

- Final exam score as a measure of achievement. This comprehensive final consists of 80 multiple choice and matching questions that are aligned with the course learning outcomes. The exam questions are reviewed and revised each year by all instructors teaching the on-campus version of the course. There are no notes allowed and no time limit for this exam.

- Quiz average as a measure of effort. The 38 assigned credit quizzes with 10 questions each have no time limit and can only be taken once. They are open book and open notes. The quiz questions are reviewed and revised each year by a committee consisting of the instructor and senior teaching assistants. Students can also seek assistance from the Stat tutors when taking these quizzes.

- Course satisfaction. This rating is obtained from the results of a survey given after course completion. It is the sum of ratings given for satisfaction with course materials, instructor, and tutors (see Appendix D).

The following were the control variables of interest:

- Age, in years, obtained from the Independent Study database

- Gender, obtained from the Independent Study database

- ACT Math score, obtained from the Independent Study database

- High school GPA, obtained from the Independent Study database

- Perceived usefulness of statistics, measured by pre-course survey (see Appendix E)

- Confidence in learning statistics, measured by pre-course survey (see Appendix E)

- Learner autonomy, measured by pre-course survey (see Appendix E)

Data Analysis

To describe the characteristics of the participants in the study, the distributions of the outcome, explanatory, and control variables were examined using SPSS 25 and JMP 13. To investigate the relationship between the explanatory variable and the outcome variables, a one-way analysis of variance (ANOVA) was performed for each quantitative outcome variables (e.g. final exam score) and a chi-square test for completion status. Because the quantitative outcome

variables were expected to be highly correlated, a multivariate analysis of covariance (MANCOVA) was used to estimate and test the parameters of the following model

$$Y_i = \beta_0 + \beta_1 \text{ Treatment} + \beta_2 \text{ Gender} + \beta_3 \text{ Age} + \beta_4 \text{ GPA} + \beta_5 \text{ ACT} + \beta_6 \text{ Stat Usefulness} +$$

$$\beta_7 \text{ Stat Confidence} + \beta_8 \text{ Learner Autonomy} + \beta_9 \text{ Treatment} \times \text{Gender} + \qquad (1)$$

$$\beta_{10} \text{ Treatment} \times \text{Age} + \beta_{11} \text{ Gender} \times \text{Age} + \beta_{12} \text{ Treatment} \times \text{Learner Autonomy} + \varepsilon$$

where Y_i : Final exam score, Average quiz score, and Course satisfaction rating. Treatment consisted of the following four groups: Control, Email, Discussion Board, and Email and Discussion Board. Logistic regression was used to predict course completion using model (1) above. The analyses were performed with and without outliers and when the results were similar, the findings with the outliers were discussed. The assumptions of the statistical procedures used in the analyses were also checked and verified.

Findings

Univariate and Bivariate Analysis

A total of 1,062 students were enrolled in the course and 594 (55.93%) consented to participate in the study. Of the study participants, 57.6% completed the course and 64.6% were female. The mean age of these participants was 27.82 years with standard deviation 9.68, the youngest was 14 years old and the oldest was 66 years old. For the 130 participants who provided this information, their mean ACT Math score was 25.27 with standard deviation 4.78, the minimum score was 15 with a maximum score of 35. For the 126 participants who provided this information, the mean High School GPA was 3.59 with standard deviation 0.65–see Table 8 for details. The minimum GPA was 2.8 but it should be noted that three students in the study had high school GPA's equal to zero. These values were recoded as missing and assumed to be those of home-schooled students.

Table 8

Characteristics of Participants in the Experiment

Variable	*n*	Minimum	Maximum	Mean	*SD*
Age	594	14	66	27.82	9.68
ACT Math	130	15	35	25.27	4.78
HS GPA	126	2.8	4.00	3.59	0.65

Of the 594 students who consented to participate in the study, 26.9% were randomly assigned to the Control group, 23.4% to the Email group, 24.1% to the Discussion Board group, and 25.6% to the Email and Discussion Board group. To test for equivalence among the four groups prior to group assignment with regards to the covariates of interest, an analysis of variance (ANOVA) was conducted for Age, High school GPA, Math ACT score, Confidence in learning statistics, Opinion on the usefulness of statistics, and Learner autonomy. The only significant ANOVA result was that for Confidence in learning statistics ($p = .012$): students assigned to the Email group had the highest confidence in learning statistics (Mean = 12.89) while those assigned to the Email and Discussion Board group had the lowest confidence in learning statistics (Mean = 11.51). Table 9 summarizes the ANOVA results.

A chi-square test of homogeneity for Group and Gender was not significant ($p = .830$). And a chi-square test of homogeneity for Group and Completion Status also yielded a non-significant result ($p = .718$). However, an interesting pattern emerged when the responses of the participants to the Discussion Board treatment were taken into account. The members of the Discussion Board group were all sent an invitation email to participate in the discussion of a given topic and a link to the Discussion Board was given in the email. A participant had three options: ignore the link (No view), view the question posted and not respond (View Only), or view and respond to the posted question (Responded). To account for these actions that were self-selected by the participants, the Treatment group was further sub-divided into eight groups:

Table 9

Comparison of Participants for Testing Baseline Equivalence of Intent-to-treat Grouping

Variable	All participants	Control group	Email group	Discussion Board group	Email and Discussion Board group	p
Age						.165
n	594	160	139	143	152	
Mean	27.82	26.93	26.96	28.45	28.94	
(SD)	(9.68)	(8.63)	(8.71)	(10.26)	(10.86)	
High School GPA						.407
n	126	27	33	38	28	
Mean	3.59	3.55	3.68	3.56	3.55	
(SD)	(0.65)	(0.34)	(0.35	(0.33)	(0.45)	
Math ACT score						.200
n	130	30	33	39	28	
Mean	25.27	25.07	26.79	24.64	24.57	
(SD)	(4.78)	(4.68)	(4.04)	(4.98)	(5.24)	
Opinion on Usefulness of Statistics						.451
n	500	139	111	122	128	
Mean	12.59	12.99	12.70	12.43	12.20	
(SD)	(4.16)	(3.67)	(4.08)	(4.31)	(4.55)	
Confidence in Learning Statistics						.012*
n	560	153	128	135	144	
Mean	12.20	12.41	12.89	12.07	11.51	
(SD)	(3.57)	(3.39)	(3.45)	(3.52)	(3.80)	
Learner Autonomy						.475
n	560	153	129	134	144	
Mean	12.20	12.06	12.41	12.11	12.23	
(SD)	(1.99)	(1.81)	(1.89)	(2.08)	(2.17)	

*significant at the .05 level

- Control

- Discussion/No view

- Discussion/View only

- Discussion/Responded

- Email

- Email and Discussion/No view

- Email and Discussion/View only

- Email and Discussion/Responded

In examining the two-way table for completion status and the new Treatment grouping above (called treatment-on-the-treated) to determine which categories to combine, an interesting pattern emerged–see Table 10. Post-hoc analysis of completion rates for these eight groups showed that participants in the Discussion/No view, Discussion/View Only, and Email and Discussion/View Only groups had a completion rate of about 50%; participants in the Control, Email, and Email and Discussion/No view groups had a completion rate of about 60%; while participants in the Discussion/Responded and Email & Discussion/Responded groups had a completion rate of about 75%. A chi-square test of homogeneity for this treatment-on-the-treated grouping and completion status yielded a non-significant result at the .05 significance level ($p = .074$). This paper also looked into the effect of this new grouping (subgroups with 50% completion rate, subgroups with 60% completion rate, and subgroups with 75% completion rate) on the response variables after controlling for the effects of the covariates of interest. These results will be compared with those of the original treatment groups which are now called intent-to-treat grouping: Control, Email, Discussion, and Email and Discussion.

Table 10

Two-way Table for Completion Status and Treatment-on-the-treated

Grouping Group/Completion status	Completed course	Did not complete course	Total
Control group			
n	93	67	160
Row %	58.13	41.87	100
Discussion – No view			
n	34	34	68
Row %	50	50	100
Discussion – View only			
n	31	27	58
Row %	53.45	46.55	100
Discussion – Responded			
n	13	4	17
Row %	76.47	23.53	100
Email			
n	85	54	139
Row %	61.15	38.85	100
Email & Discussion – no view			
n	47	33	80
Row %	58.75	41.25	100
Email & Discussion – view only			
n	33	31	64
Row %	51.56	48.44	100
Email & Discussion – responded			
n	6	2	8
Row %	75	25	100
Total			
n	342	252	594
Row %	57.58	42.42	100

Source: SPSS version 25.

An ANOVA comparing student performance and course satisfaction showed no significant difference among students at the end of the course in the intent-to-treat grouping: the p-values for final exam, average quiz, and course satisfaction were .268, .343, and .586 respectively, see Table 11. There was also no significant difference among students at the end of the course in the treatment-on-the-treated grouping, see Table 12.

Table 11

Summary of Student Performance and Satisfaction by Intent-to-treat Grouping

Variable/Group	All participants	Control group	Email group	Discussion group	Email & Discussion	*p*
Final Exam						.268
n	342	93	85	78	86	
Mean	.788	.789	.804	.795	.765	
(*SD*)	(.136)	(.142)	(.118)	(.137)	(.146)	
Average quiz						.343
n	343	95	84	80	84	
Mean	.955	.957	.986	.943	.951	
(*SD*)	(.089)	(.066)	(.057)	(.129)	(.093)	
Course satisfaction						.586
n	296	85	75	72	64	
Mean	14.03	13.92	14.147	14.31	13.73	
(*SD*)	(2.60)	(2.77)	(2.57)	(2.38)	(2.66)	

Source: SPSS version 25.

Table 12

Summary of Student Performance and Satisfaction by Treatment-on-the-treated Grouping

Variable/Group	All participants	Control group	No view ED60	View Only ED50	Responded ED75	p
Final Exam						.462
n	342	93	132	98	19	
Mean	.788	.789	.785	.781	.836	
(*SD*)	(.136)	(.142)	(.123)	(.149)	(.125)	
Average quiz						.142
n	343	95	130	100	18	
Mean	.955	.957	.961	.940	.985	
(*SD*)	(.089)	(.066)	(.075)	(.125)	(.028)	
Course satisfaction						.691
n	296	85	108	86	17	
Mean	14.03	13.92	14.05	14.23	13.47	
(*SD*)	(2.60)	(2.77)	(2.54)	(2.46)	(2.85)	

Source: SPSS version 25.

Figure 3 shows the boxplots of the outcome variables by the intent-to-treat grouping. The same analysis was used for the treatment-on-the-treated grouping and Figure 4 shows the boxplots of the outcome variables by the treatment-on-the treated grouping. The presence of outliers and the small sample sizes for the students who responded to the postings might complicate the interpretations of these results. Twenty nine students responded to the discussion board postings, 23 answered the first posting and 12 responded to the second posting. The number of respondents gradually tapered off after the seventh posting. Seventeen students participated in the discussion board once, four participated twice, and another four participated thrice. Two students responded to seven of the nine postings.
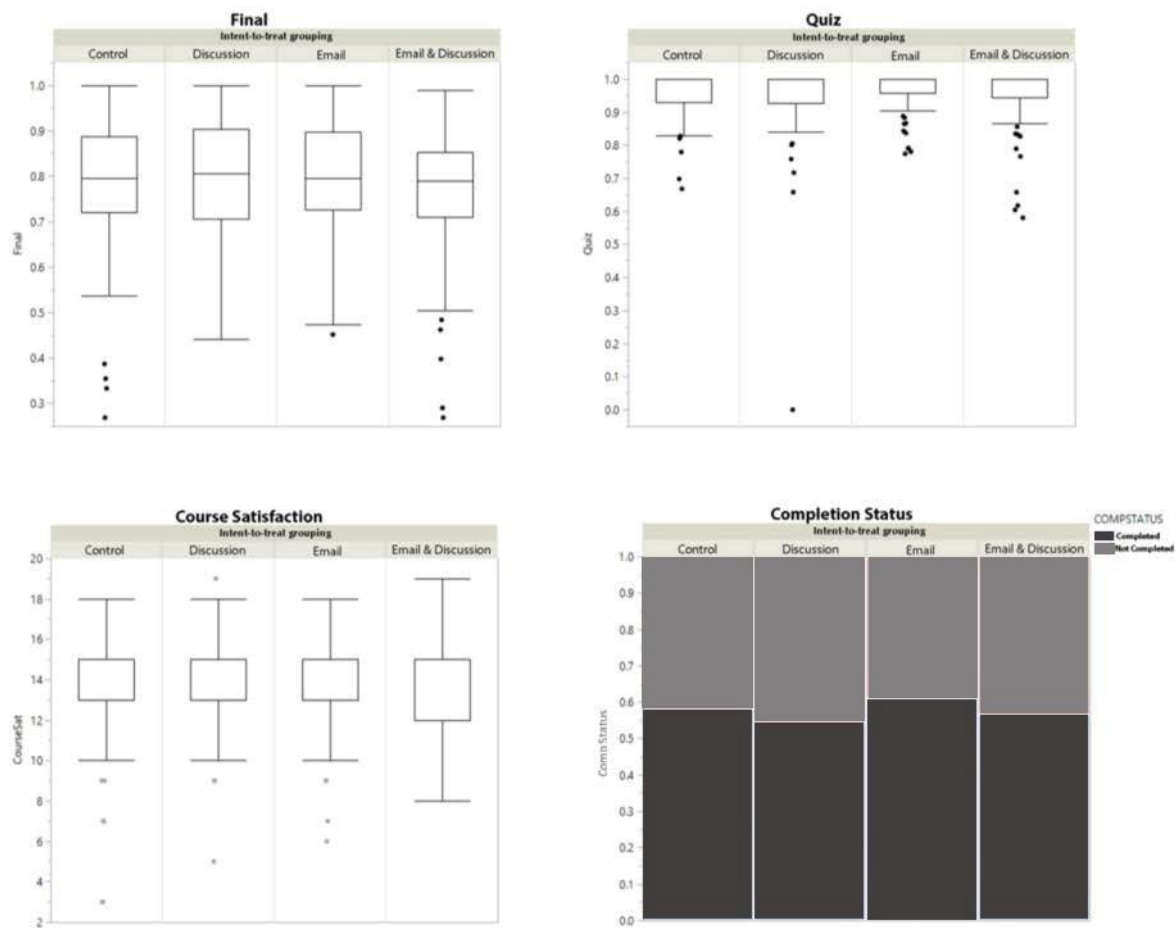
Figure 3. Distribution of outcome variables by intent-to-treat grouping.
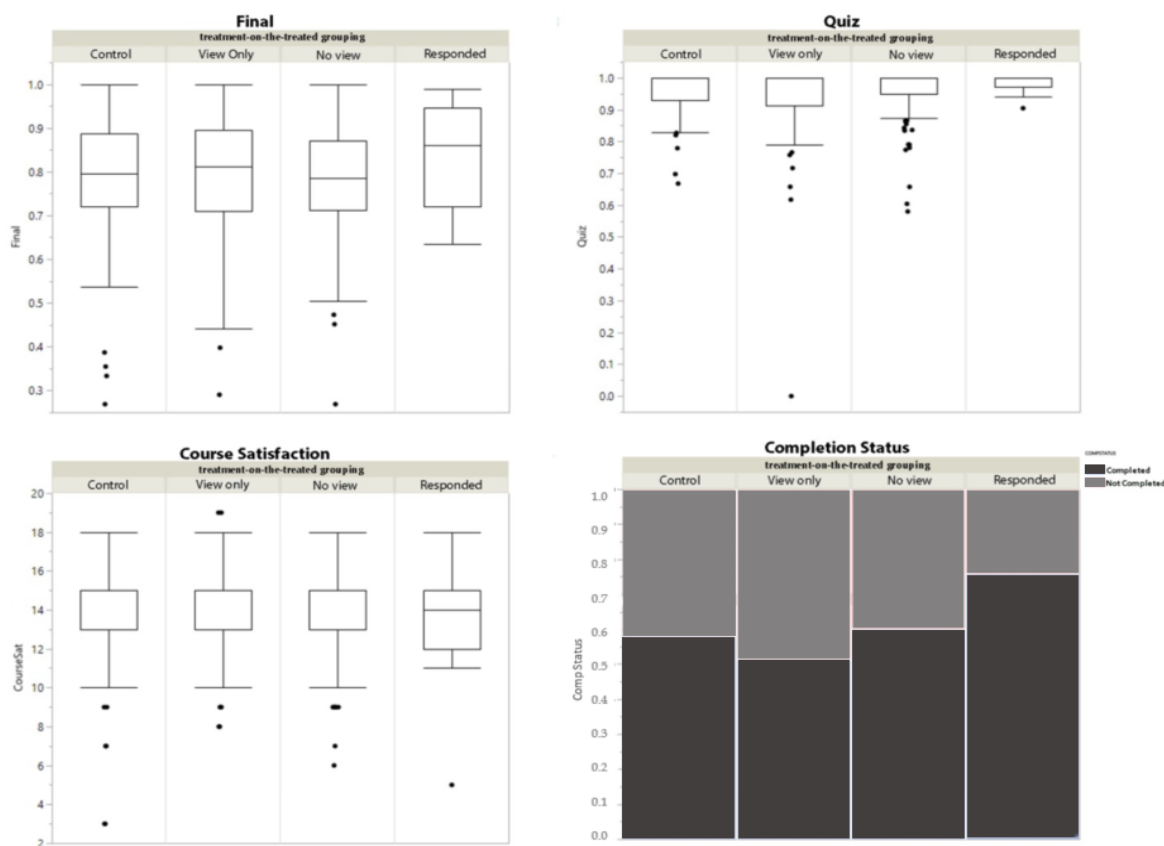
Figure 4. Distribution of outcome variables by treatment-on-the-treated grouping.

MANCOVA Results

To determine if the effects of the different treatment groups are statistically significant after the effects of the control variables are taken into account, a general linear model (GLM) analysis was used in SPSS 25 and JMP 13. An examination of the correlation matrix for the three quantitative outcome variables showed that they were highly correlated: the correlation coefficients ranged from .266 for Course satisfaction and Average Individual quiz scores to .585 for Average Individual quiz and Final exam scores. All of these values are significant at the .01 level and MANCOVA was used to find any group differences based on a linear combination of the outcome variables after controlling for the effects of the covariates of interest.

An initial MANCOVA model was analyzed in SPSS 25 using the eight main effects, four interaction terms in the specified model, and three outcome variables. Inclusion of all three outcome variables in the analyses would provide the maximum amount of information regarding the effect of the explanatory variable, intent-to-treat grouping. However, the model was fit with $n = 60$. This small sample size was the result of High school GPA and Math ACT having 78% missing data. The following results are from the listwise deletion approach used by SPSS 25 without High school GPA and Math ACT scores.

Intent-to-treat grouping. The analysis of model (2) below was based on $n = 241$. $Y_i = \beta_0 + \beta_1$ Treatment $+ \beta_2$ Gender $+ \beta_3$ Age $+ \beta_4$ Stat Usefulness $+$

$$\beta_5 \text{ Stat Confidence} + \beta_6 \text{ Learner Autonomy} + \beta_7 \text{ Treatment} \times \text{Gender} + \quad (2)$$

$$\beta_8 \text{ Treatment} \times \text{Age} + \beta_9 \text{ Gender} \times \text{Age} + \beta_{10} \text{ Treatment} \times \text{Learner Autonomy} + \varepsilon$$

The MANCOVA results for model (2) had a multivariate R^2 of at least 14% as it is the highest univariate r^2. The univariate values of r^2 were .140, .143, and .119 for Final Exam, Average Quiz, and Course satisfaction, respectively. The MANCOVA results for this model had a significant Box's test of equality of covariance ($p = .019$) so Pillai's Trace was used instead of Wilk's lambda. It also had a non-significant Levene's test of equality of error variances for Final Exam and Course satisfaction: $F(7, 233) = 0.768$, $p = .615$ and $F(7, 233) = 0.892$, $p = .513$ respectively, and a significant result for Average Quiz $F(7, 233) = 2.483$, $p = .018$ so the assumption of homogeneity of variances is partially met. The assumptions of independence, linearity among the dependent variables, multi-collinearity, and equality of regression slopes were looked into and, except for non-normality, no significant violation was found. In addition, the MANCOVA test procedures are robust against the violation of the normality assumption for

large sample sizes. This study's sample size of 241 with six explanatory variables of interest is large enough to invoke the Central Limit Theorem (Rencher & Christensen, 2012).

The MANCOVA tests showed a significant omnibus effect for two of the six main effects and none for the four 2-way interactions of interest on the multivariate space defined by the three outcome variables. The two significant main effects were intent-to-treat grouping and confidence in learning statistics–see Table 13. As indicator of effect size, partial eta-squared values for these main effects were obtained, which were .025 and .039, respectively. These values are below the .0588 benchmark for medium effect size (Cohen, 1969). The power of the test for intent-to-treat grouping is .843 which indicates that we have sufficient power to detect a significant difference. However the statistical power for the test involving confidence in learning statistics is .697 which is below the widely accepted minimum value of .80 for sufficient power.

Table 13

MANCOVA Results for Specified Model Combining All Three Outcome Variables for Intent-to-treat Grouping

Variables	Pillai's Trace	p
Intent-to-treat Grouping	.076	.045*
Gender	.010	.526
Age	.021	.197
Stat Confidence	.039	.033*
Stat Usefulness	.016	.322
Learner Autonomy	.007	.696
Group × Gender	.036	.515
Group × Age	.032	.621
Group × Autonomy	.054	.207
Gender × Age	.012	.455

*significant at the .05 level. Source: SPSS 25.

Examining the univariate results, we found that after accounting for the effects of the covariates of interest, the intent-to-treat grouping had a highly significant effect on quiz scores

(p = .008) and confidence in learning statistics had a significant positive effect on final exam

scores (p = .007). This latter finding indicate that students who had higher confidence in

learning statistics had higher final exam scores. The estimated marginal means of quiz scores

and the other two outcome variables for the intent-to-treat grouping are given in Table 14. It

appears that students assigned to the Discussion group had the lowest average quiz scores (93%)

while students assigned to the email group had the highest average quiz scores (97%).

Table 14

Estimated Marginal Means of Outcome Variables for Intent-to-treat Grouping after Accounting for the Covariates

Outcome variable	Group	Mean*	Standard error	95% *CI*
Final exam	Control	.778	.016	[.746, .810]
	Discussion	.788	.017	[.755, .822]
	Email	.796	.017	[.762, .829]
	Email & Discussion	.774	.016	[.742, .806]
Average quiz	Control	.952	.011	[.930, .973]
	Discussion	.931	.011	[.908, .953]
	Email	.970	.012	[.947, .993]
	Email & Discussion	.950	.011	[.929, .972]
Course satisfaction rating	Control	13.754	.341	[13.082, 14.426]
	Discussion	14.241	.353	[13.545, 14.938]
	Email	14.149	.355	[13.449, 14.848]
	Email & Discussion	13.822	.359	[13.115, 14.530]

Note: CI = confidence interval. *Covariates appearing in the model are evaluated at the following values: Age = 28.53, Stat Usefulness = 12.4153, Stat Confidence = 12.4355, Learner Autonomy = 12.5056. Source: SPSS 25.

Treatment-on-the-treated grouping. The MANCOVA results for model (2) had a

multivariate R^2 of at least 16%: the univariate values of r^2 were 16% for Final Exam, 11% for

Average Quiz, and 11% for Course satisfaction. The MANCOVA results for this model had a

non-significant Box's test of equality of covariance ($p = .122$) so Wilks' Lambda was used for

testing. It also had a non-significant Levene's test of equality of error variances for final exam:

$F(7, 233) = 1.335$, $p = .235$; Course satisfaction: $F(7, 233) = .500$, $p = .834$; and Average Quiz

score: $F(7, 233) = 1.253$, $p = .275$ so the assumption of homogeneity of variances is met. The

assumptions of independence, linearity among the dependent variables, multicollinearity, and

equality of regression slopes were looked into and, except for non-normality, no significant

violation was found. The MANCOVA tests showed a significant omnibus effect for one of the

six main effects and none for the four 2-way interactions of interest on the multivariate space

defined by the three outcome variables. The only significant main effect was confidence in

learning statistics–see Table 15. This covariate had a small effect size (partial eta-squared =

.047) and a statistical power of .792. Examining the univariate results, we find that after

accounting for the effects of the covariates of interest, the student's confidence in learning

statistics had a significant positive effect on the final exam scores ($p = .003$) and course

satisfaction ratings ($p = .026$). These findings indicate that students who have higher confidence

in learning statistics had higher final exam scores and gave the course higher ratings, on average.

Table 15

MANCOVA Results for Specified Model Combining All Three Outcome Variables for Treatment-on-the-treated Grouping

Variables	Wilks' Lambda	p
Treatment on the treated	.966	.578
Gender	.995	.770
Age	.992	.606
Stat Confidence	.953	.014*
Stat Usefulness	.986	.387
Learner Autonomy	.994	.727
Group × Gender	.940	.135
Group × Age	.976	.794
Group × Autonomy	.981	.901
Gender × Age	.986	.364

*significant at the .05 level. Source: SPSS 25.

Logistic Regression Results

Binary logistic regression in JMP 13 was used to examine the likelihood that students complete the course for the intent-to-treat grouping only because the treatment-on-the-treated grouping was formed using completion status. Results discussed below are for $n = 495$ with High school GPA and and Math ACT scores excluded in the analyses. The specified model is

$$Y_i = \beta_0 + \beta_1 \text{ Treatment} + \beta_2 \text{ Gender} + \beta_3 \text{ Age} + \beta_4 \text{ Stat Usefulness} +$$

$$\beta_5 \text{ Stat Confidence} + \beta_6 \text{ Learner Autonomy} + \beta_7 \text{ Treatment} \times \text{ Gender} + \quad (3)$$

$$\beta_8 \text{ Treatment} \times \text{ Age} + \beta_9 \text{ Gender} \times \text{ Age} + \beta_{10} \text{ Treatment} \times \text{ Learner Autonomy} + \varepsilon_i$$

where Y_i is the logit for completion. There were three significant predictors of completion status in this study when accounting for the presence of the specified covariates: a student's opinion on the usefulness of statistics, age, and confidence in learning the subject. Table 16 shows these results with maximum likelihood estimates for model (3).

Table 16

Summary of Logistic Regression Results for Specified Model (3)

Variables	Likelihood ratio Chi-square	p
Intent-to-treat Grouping	0.967	.809
Gender	1.299	.254
Age	5.538	.018*
Stat Confidence	4.021	.045*
Stat Usefulness	7.239	.007*
Learner Autonomy	0.695	.404
Group × Gender	2.831	.418
Group ×Age	3.076	.380
Group ×Autonomy	1.171	.759
Gender ×Age	2.887	.089

* significant at the .05 level. Source: JMP 13.

Students who think statistics is not useful have a higher likelihood of completing the course while students who have a higher level of confidence in learning statistics are more likely to complete the course. The former finding is contrary to the expected result based on theory but it maybe that there are more factors that account for completion status which are not included in model (3). This specified model explained 7% of the variance in completion status (Nagelkerke's R^2) which implies that there are other variables that affect completion status that were not taken into account. The model correctly classified 60% of the completion status for students in the study, with an 83% success rate for predicting those who will complete the course and a 28% success rate for predicting those who will not complete the course. The logistic regression plots exhibited in Figure 5 show the effect of perceived usefulness of statistics, confidence in learning statistics, and age on the cumulative predicted probabilities of completing the course. The plots show a negative relationship between perceived usefulness of statistics and probability of course completion and a positive relationship between confidence in learning statistics and likelihood of completing the course. They also show that older students have a

higher probability of completing the course. The odds ratios and 95% confidence intervals of the odds ratios for the significant predictors are given in Table 17. For example, for every one unit increase in perceived usefulness of statistics, the odds of completion decrease by about 6.32%.

Table 17

Odds Ratios for Significant Predictors in Logistic Regression Model for Odds of Completion versus Non-completion

Variables	Odds Ratio	95% *CI*
Stat Usefulness	0.936	[0.889, 0.986]
Stat Confidence	1.070	[1.009, 1.135]
Age	1.029	[1.003, 1.055]
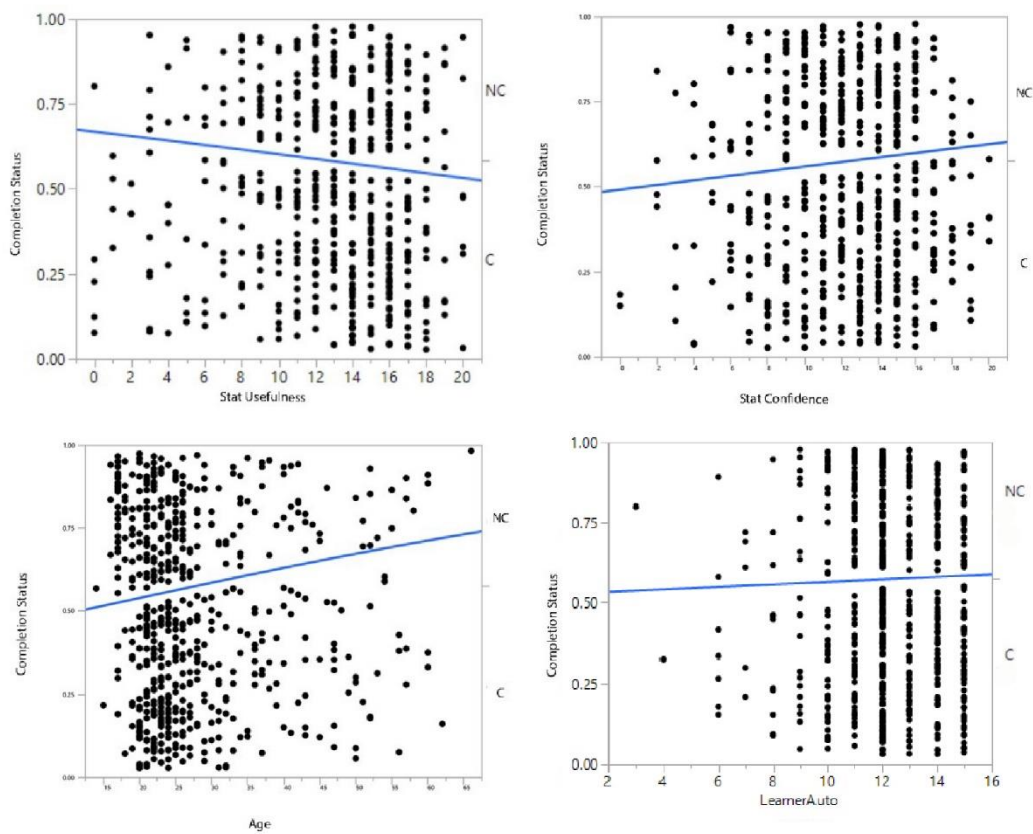
Figure 5. Logistic plots for completion status by covariates of interest. C= completed, NC= not completed.

Discussion and Implications

Discussion

This study adds to the body of research literature examining the importance of instructional dialogue in online distance education and the factors affecting learner performance and satisfaction. A randomized, controlled, and double-blinded experiment was used to investigate the impact of enhanced educational dialogue, in terms of reminder emails and discussion board participation, on student performance and course satisfaction. Participants in the study were randomly assigned to different types and levels of educational dialogue and their completion status, final exam scores, average quiz scores, and course satisfaction ratings were compared after controlling for these covariates of interest: age, gender, learner autonomy, opinion on perceived usefulness of statistics, and confidence in learning statistics. Abbreviated measures of the last three constructs that were developed and validated by the principal investigator were used in the analysis. The presence of 78% missing data for the covariates high school GPA and Math ACT scores resulted in the decision to exclude these control variables in the MANCOVA and logistic regression models. A complication arose when the participants assigned to the discussion board had three options for participation: they could choose to not view the discussion board questions, choose to view only, or choose to respond. This study took these options into account and ran an analysis of this new grouping, called treatment-on-the-treated. The original grouping was called intent-to-treat and the results of these two groupings on student performance and course satisfaction were compared. The intent-to-treat grouping and confidence in learning statistics had significant effects on student achievement and satisfaction. The treatment-on-the treated grouping did not yield a significant result.

The MANCOVA results showed that students who have higher confidence in learning statistics had higher final exam scores and gave the course higher satisfaction ratings. The findings also showed that students assigned to the Email group had the highest average quiz scores (97%) while students assigned to the Discussion group had the lowest average quiz scores (93%). Recall that quiz scores are indicators of student effort because students can use their book, class notes, and they can also seek help from tutors when taking their quizzes. The result for the Discussion group might be due to the fact that not all participants assigned to this group took advantage of the discussion board. In fact, only 12% of those assigned to the Discussion Only group responded to the postings. This might account for the lower quiz scores (which is an indicator of effort expended in the course) for students in this group.

The logistic regression results showed that older students and those who have high confidence in learning statistics were more likely to complete the course while those who think statistics is useful were less likely to complete the course. The last finding is contrary to theory based on the literature review and may be due to the fact that completion status depends on many other factors beyond the control of the instructor (Rovai, 2003).

Learner autonomy was not a significant predictor of student success in this study. This might be due to the nature of the course which can be completed within 12-15 months. Time management, motivation, and intent to prepare well may not contribute to success as much as in online semester-long online courses. In addition, learner autonomy as defined in this study pertains to plans to study well and to prepare well for exams, and not needing external rewards to feel motivated. These findings suggests that a better measure of learner autonomy needs to be developed. Gender was not a significant predictor of student success when its effect was examined in the presence of the other control variables.

Recommendations for future research include looking at time-to-completion as an outcome variable. Preliminary analyses show that this might be worth investigating in relation to learner autonomy. Time to completion might also act as an early warning system for students who are at greater risk of not completing the course. The Independent Study team also suggested that the reason for taking the course be added as an explanatory variable for future research because it might be predictive of student success in the course. In addition, a few emails from students in the Email group were received requesting to stop sending reminder emails on the 15th and 29th day of the month. This study shows that there might be some advantage in sending these reminder emails, students in this group had the highest average quiz scores. However, in the future, we suggest continuing these email reminders once a month for each individual student: this means that if a student enrolls on June 20 and they have not submitted any quiz for the last 30 days, a reminder email will be sent on July 20 to this particular student. This way the reminders are more personalized and might encourage more students to act on the reminder. Further, instead of using the study's specified model for analysis, a best model derived after investigating all main effects and all two-way interactions might yield higher predictive power. A preliminary analysis shows a higher R^2 and the presence of some significant interaction terms like age and usefulness of statistics, gender and learner autonomy, and age and learner autonomy.

Implications

One of the implications of this study is that basic course progress feedback to students with minimal teacher-student interaction may have an impact on student achievement. Sending regular emails regarding course progress seem to have a positive effect on credit quiz performance, it is a low cost intervention with potential benefits in large online courses as shown

in this study. Discussion board participation seem to be beneficial even in this particular independent study setting. It can possibly be offered as an extra credit in similar courses. Interaction need not be personal, especially in large online courses so long as there's a student perception that their performance is being monitored and that they are getting feedback and guidance (Hawkins, 2013; Roblyer, 2006).

Valid, reliable and abbreviated scales for attitude towards statistics can also be strong predictors of student achievement in introductory statistics courses. Further research is needed on the impact of confidence in learning statistics on student performance and satisfaction. In addition, online distance education course designers might look into instructional interventions to facilitate improvements in self-efficacy or confidence in learning introductory statistics (Schunk, 1991; Zimmerman, 2000). Instructors can incorporate more opportunities for practice and feedback when designing their courses to foster student confidence in learning.

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DISSERTATION CONCLUSION

The results of this study can only be generalized to undergraduate students studying introductory statistics. They may not apply to graduate school or high school students and other subjects like history or biology.

Overall, the completion rate for this study (57%) is higher compared to the previous section of the course (51%) and a two-sample z-test for these two proportions was significant with $p = .0044$. Students who are older and have higher confidence in learning statistics were more likely to finish the course. An analysis of the survey results given to those who did not complete the course showed that some of the reasons students dropped out of the course were: course was more difficult than expected (29%), did not finish in time (24%), an unexpected event happened leaving no time for the class (21%), switched to conventional course setting rather than online (10%), changed major and did not need the class anymore (5%), and difficulty with course mechanics (5%). Except for the last one, most of these reasons are beyond the control of the course administrators.

Based on the MANCOVA results, the chosen interventions were effective in improving student performance and course satisfaction overall. Students assigned to the email group had the highest average quiz scores (see Table 3.3). This finding supports the claims of Lehman, Kauffman, White, Horn, and Bruning (2001); Lemak, Shin, Reed, and Montgomery (2005); and Simpson (2003) that the use of email enhanced the educational experience and such contacts did not need to be personalized to be successful. Minimal email exchanges can be useful and might be the only viable option for enhanced educational dialogue in large classes with at least 1000 students. Regarding the use of discussion boards to enhance teaching presence, this study showed none of its potential benefit in an independent study setting. In this course, students

finish the year-long course at their own pace and student-to-student interaction is difficult to achieve in real time. Students might not be inclined to respond to a posting that might be a month old. Overall, the chosen interventions did not influence completion status. But students who were older and had a higher confidence in learning statistics were more likely to complete the course. For those who completed the course, the email group had the highest average quiz scores. And those students who had higher confidence in learning statistics had higher final exam scores and higher course satisfaction.

For scale development, this study showed that having no mix of positive and negative items can result in valid and reliable scales. There is less confusion when researchers don't have to deal with reversing negative items. In addition, 6-point Likert scales and factors with at least three items can be adequate measures. There is no need for long questionnaires if the selected items measure precisely the construct of interest after content validity of the items has been established.

Practitioners can use the abbreviated scales developed for this study with some degree of confidence, especially the scales measuring perceived usefulness of statistics and confidence in learning statistics. They can use these scales to track whether student attitudes change in the course of study. They can also use this information when developing learning activities by adding results of current studies from the media and incorporating multiple practice and feedback activities to increase confidence in learning statistics. Measuring learning autonomy is still a challenging endeavor. Future research should include a more precise definition of this construct.

APPENDIX A:

Extended Literature Review

Introduction

This extended literature review covers research pertinent to online distance education for undergraduate students with emphasis on introductory statistics courses. It provides context for the research beyond that which is reported in the two articles. It will focus on the following topics:

- Theories in online distance education

- Research behind chosen interventions in study

- Characteristics of successful students in online distance education courses

- Characteristics of successful students in introductory statistics courses

- Existing measures of constructs of interest

Theories in Online Distance Education

Distance education, defined as "all forms of education in which all or most of the teaching is conducted in a different space than the learning, with the effect that all or most of the communication between teachers and learners is through a communications technology" (p. xiv, Moore, 2003), had its beginnings in the United States in the late 1800s as mail correspondence courses (Saba, 2003). Since then, distance education courses have used the medium of radio, film, television, satellites, and computer-mediated-communications (Oviatt, 2017). There has been an exponential increase in online distance education course enrollment, especially with the advent of massive open online courses known as MOOCs with an average enrolment of 43,000 students (Jordan, 2014). The context of this research is an independent study program where at least a thousand undergraduate students take an introductory statistics course for 12-15 months.

Since their inception, online distance education courses have been plagued with lower completion rates, lower passing rates, and lower course satisfaction ratings when compared with

face-to-face instruction (Carr, 2000; Diaz, 2002; Morgan & Tam, 1999; Morris, Finnegan, &

Wu, 2005; Rovai, 2003; Waschull, 2001). Garrison (1987) claimed that no area of research in

distance education has received more attention than student attrition. The early distance

education researchers and practitioners focused on best practices to improve course completion

and student performance but this approach led to the neglect of theory (Moore, 2003; Saba,

2003). To address this deficiency, leading distance education scholars put forth the main

theoretical frameworks underpinning distance education theory with the publication of

Contemporary Issues in American Distance Education in 1990 and the Handbook of Distance

Education in 2003. As opposed to the practitioners' preoccupation with the best technology to

adopt, the leading theorists in the field emphasized the centrality of the learner and his or her

interaction with teachers and peers. The three major theories that are discussed in detail in the

following sections are Moore's transactional distance theory, Garrison's community of inquiry,

and Anderson's theory of educational interactions.

Borje Holmberg claimed that "Personal relations, study pleasure, and empathy between

students and those supporting them (tutors and counselors) are central to learning in distance

education. Feelings of empathy and belonging promote students' motivation to learn,

influencing learning favorably" (p. 65, Simonson, Schlosser, & Orellana, 1999).

Charles Wedemeyer, a professor from the University of Wisconsin as quoted by Keegan

(1986), considered the independence of students as the essence of distance education. He also

preferred the term "independent study" for distance education at the post-secondary level. He set

forth a system of distance education that emphasized learner independence and the use of

technology as a way of implementing it. According to Simonson et al. (1999), Wedemeyer

believed that "the development of the student-teacher relationship was key to the success of distance education" (p. 64).

Transactional Distance Theory

Michael Moore (1993) built on Wedemeyer's claims and posited the theory of transactional distance which defined the relationships among teacher, student, and course structure. First, he defined transactional distance as "a psychological and communications space to be crossed, a space of potential misunderstanding between the inputs of the instructor and those of the learner" (p. 22). This space or distance is a continuous variable which is relative rather than absolute and can occur in both traditional and distance education instruction but even more so in the latter. There are also varying degrees of transactional distance within distance education programs. The theory claims that "distance is not simply a geographic separation of learners but is a pedagogical concept" (p. 22) which describes all possible relationships between teacher and learners when they are separated by space and/or time. Moore claimed that the "purpose of distance education theory is to summarize the different relationships and strength of relationships among and between the variables that make up transactional distance, especially the behaviors of teachers and learners" (p. 23). Second, he identified three variables that affect transactional distance between learners and teachers: instructional dialogue, program structure, and learner autonomy. These three variables will be discussed in detail next.

Instructional dialogue. Moore initially defined dialogue as a positive interaction between teacher and learner that leads to improved student understanding. It is a qualitative variable that is used to describe an interaction or series of interactions having positive qualities that other interactions might lack. There might be negative or neutral interactions but instructional dialogue applies to positive interactions. The nature and extent of the dialogue is determined by the educational philosophy of the course designers, the personalities of teacher

and learner, subject matter, and environmental factors. According to Moore, the interactive

nature of the medium of communication also affect dialogue in the teaching-learning

environment. In this regard the current online learning environment has the potential to increase

dialogue between teachers and learners and reduce transactional distance. Later on, he notes that

a form of dialogue occurs even in courses that have no interaction, such as when the student is

given printed materials, audiotapes or videotapes. He claims that even in these media "there is a

form of learner-instructor dialogue because the learner does have an internal or silent interaction

with the person who in some distant place and time organized a set of ideas or information for

transmission for what might be thought of as a virtual dialogue with an unknown distant reader,

viewer, or listener" (p. 25). Dialogue is also influenced by content and class size. For example,

science and mathematics courses use a more teacher-directed approach having less dialogue.

Group size also determine the amount and extent of interpersonal dialogue that may occur in any

instructional system (Gorsky, 2007). Large classes, consisting of more than a thousand students,

will have a minimal amount of teacher-student interaction.

Course structure. Program or course structure consists of the ways in which teaching is

structured so it can be delivered through the various communication media. It "expresses the

rigidity or flexibility of the program's educational objectives, teaching strategies, and evaluation

methods. It describes the extent to which an education program can accommodate or be

responsive to each learner's individual needs" (p. 26). According to Moore, there "appears to be

a relationship between dialogue, structure and learner autonomy, for the greater the structure and

the lower the dialogue in a program, the more autonomy the learner has to exercise" (p. 27).

Learner autonomy. The theory of transactional distance defines learner autonomy as

the process in which the student use teaching materials and teaching programs to achieve goals

of their own, in their own ways, under their own control. It is the extent to which "in the

teaching/learning relationship it is the learner rather than the teacher who determine the goals, learning experiences, and the evaluation decisions of the learning program" (p. 31). However, a program does not have to give students autonomy in all these dimensions (goals, learning experiences, and evaluation decisions) simultaneously, often times a program will only provide autonomy in one dimension. The ideal autonomous learner is a person who is emotionally independent of an instructor, who can approach subject matter directly without having a teacher intervening between the learner and the subject matter. The personal computer has opened new opportunities through its combined asynchronocity and relative lack of structure. Each student can interact with the ideas of others in his/her own time and place. Moore (1993) theorized that if instructional dialogue increased and course structure and learner autonomy decreased then transactional distance will decrease.

Research on and critique of transactional distance theory. In the past 20 years, numerous studies have sought to operationalize transactional distance and its three components, the relationship among them, and their influence on student performance. Moore (2003) and Aragon (2003) claimed that increasing instructional dialogue and teaching presence in distance education will decrease transactional distance and improve student performance and satisfaction. Lemak, Shin, Reed, and Montgomery (2005) conducted an empirical investigation regarding technology, transactional distance, and instructor effectiveness. They analyzed instructor-evaluation data from 406 distance learning students in the U.S. and concluded that transactional distance affected perceived teacher effectiveness.

Gorsky and Caspi (2005b) reviewed several studies attempting to support or validate Moore's theoretical model through empirical research. They found that either the findings partially supported the theory or those that supported the theory lacked reliability and or

construct validity. They also claimed that the theory may be reduced to a single proposition, "as

the amount of dialogue increases, transactional distance decreases" (p. 1). Giossos, Koutsouba,

Lionarakis, and Skavantzos (2009) also reviewed existing studies relating to Moore's theory and

found a variety of functional definitions of transactional distance that revealed an absence of

consensus. They suggested defining transactional distance as the distance in understanding

between teacher and learner. The proposed study focuses on examining different types and

levels of instructional dialogue applicable in large online distance education, while controlling

for learner autonomy, to improve student performance. The concepts of transactional distance

and course structure are not addressed in this study.

Community of Inquiry Theory

Tinto (1993) claimed that students who have a low sense of belonging in a community of

learners tend to feel isolated and are at a greater risk of withdrawing. Garrison, Anderson, and

Archer (2001) sought to provide a theoretical framework to explain online distance education

practice in the context of computer mediated communication (e.g. computer conferencing) to

create a community of learners at a distance. They identified three overlapping elements

(teaching presence, social presence, and cognitive presence) of a community of inquiry to create

deep and meaningful learning experiences. This paper focuses on the teaching and social

elements because they are the only aspects, in the context of this study, that can be manipulated

(unlike cognitive presence). Garrison, Anderson, and Archer (2003) defined teaching presence

as the "design, facilitation and direction of cognitive and social processes for the purpose of

realizing personally meaningful and educationally worth-while learning outcomes" (p. 116).

Teaching presence should diagnose the needs and provide timely information and direction to the

learner. Social presence is defined as the "ability of participants to identify with the course of

study and communicate purposefully in a trusting environment, and develop inter-personal

relationships" (Garrison, Cleveland-Innes, & Fung, 2010, p. 32). Because this report is based on an independent study course where students are in different stages of progress in the course, developing inter-personal relationships among the students is not the goal of the research.

Aragon (2003) emphasized that social presence is one of the most significant factors in improving instructional effectiveness and building a sense of community. Social presence has been shown to affect cognitive presence positively but online social presence does not happen automatically, it has to be structured. Teaching presence can help structure social presence by defining and initiating discussion topics and by focusing the discussion. Garrison and Cleveland-Innes (2005) concluded that "teaching presence in the form of facilitation is crucial in the success of online learning" (p. 136). It may be possible, even in relatively large classes, to structure some social presence between students and teaching assistants who can initiate and respond to student postings.

Rourke, Anderson, Garrison, & Archer (2001) provided a community of inquiry model for online learning environments using Garrison's three presence components: cognitive, social, and teaching. Picciano (2002) noted that Rourke et al. advised more research on each of these individual components and argued that "What is critical here is that presence in an online course is fundamentally a social phenomenon and manifests itself through interactions among students and instructors" (p. 24).

Wallace (2003) reported that the "consensus in studies of online community is that community can be developed in online learning environments, and that it plays an important role in student success …. however, the literature is more anecdotal and case-based "(p. 269) and no research has probed whether the existence of community is related to student learning outcomes.

The proposed study attempts to link teaching presence and social presence as components of the community of inquiry to student learning outcomes.

Theory of Online Learning Interactions

Anderson (2003) claimed that the role of interaction is a crucial element of the education process. He quoted Daniel and Marquis' seminal article in 1979 challenging distance education educators to "get the mixture right between independent study and interactive learning" (p. 1). He used Wagner's definition of interaction as "reciprocal events that require at least two object and two actions. Interactions occur when these objects and events mutually influence one another" (p. 11). He expounded on the nature and importance of six forms of educational interactions: student-student, student-teacher, student-content, teacher-teacher, teacher-content, and content-content. He also pointed out that interaction within a community of inquiry binds learners in time and are generally more expensive and challenging to scale to a large number of students.

Fredericksen, Pickett, Shea, Pelz, and Swan (2000) reported that the most significant explanatory variable for learning in an online course was students' interaction with the teacher. In a survey of 1,406 students enrolled in their online on-campus courses, "students who reported the highest levels of interaction with the teacher also reported the highest levels of perceived learning in the course (p. 18). In their review of the literature regarding interactions in distance education, Thurmond and Wambach(2004) reported several multiple stepwise regression results which indicated that learner-instructor interaction was the most significant predictor of perceived learning. Hay, Hodgkinson, Peltier, and Drago (2004) showed that instructor-student interaction was stronger than student-student interaction in terms of predicting effectiveness for both online and traditional courses. Swan (2001) also found that "interaction with instructors seemed to

have a much larger effect on satisfaction and perceived learning than interaction with peers" (p. 322).

Other Theories of Instruction in Distance Education

Gorsky and Caspi (2005a) and Caspi and Gorsky (2006) proposed a unified theory of instruction. They laid out two propositions: "first, every element in an instructional system is either a dialogue or a resource which supports dialogue, and second, dialogue and learning outcomes are correlated" (2006, p. 736). The second proposition laid out by Gorsky and Caspi (2005a) is that dialogue is correlated with learning outcomes, specifically, student achievement and satisfaction. Gorsky, Caspi, and Smidt (2007) conducted a study regarding the use of instructional dialogue in a distance education physics course and found that a large majority of students turned to their instructors for assistance and not to their fellow students. Their study involved sending 124 students in their advanced Quantum Study course a questionnaire. They concluded that adult, distance education students learned primarily from self-instruction texts and tutorials and only sought help when they encountered some difficulties. When the course was relatively easy they turned to their peers but when the course was deemed difficult or advanced, they turned to their instructors or tutors. Instructor-student dialogues were used as a last resort. According to Gorsky et al. (2007),

> Some general theories of instruction, such as those advanced by Bruner (1966) and Rogers (1969), and some theories of distance education (Moore, 1993; Garrison & Anderson, 2003), often assign to interpersonal dialogue, especially between teacher and student, an importance that may not be realized in practice. (p. 6)

Anderson (2008) also looked at developing more useful theories of online learning and referenced Bransford, Brown, and Cocking's (1999) four overlapping aspects of learning environments: learner centered, assessment centered, knowledge centered, and community

centered. He suggests that "learner-centered activities make extensive use of diagnostic tools and activities, so that these pre-existing knowledge structures are made visible to both the teacher and the student" (p. 35) and to use "strategies that are designed to provide formative and summative assessment with minimal direct impact on teacher workload" (p. 38*).* In the context of this independent study course, periodic email feedback on student achievement acts as a diagnostic tool that might be beneficial to students.

In summary, various distance education theories have emphasized the importance of student-teacher interaction for success in online distance education courses. However, as defined by these theories, interaction is a mutual two-way communication between students and teachers or teaching assistants. In large online distance education courses, a positive two-way interaction or dialogue may not be possible and pseudo-interaction in terms of automated email messages based on student performance and periodic invitations to participate in a discussion board initiated and facilitated by teaching assistants may be enough to provide a sense of belonging and community that might impact student performance and course satisfaction.

Research Behind Chosen Interventions

The majority of empirical studies conducted in distance education involve observational studies and quasi-experiments comparing online distance education with classroom-based courses (Summers, Waigandt, & Whittaker, 2005; Thurmond & Wambach, 2004; Waschull, 2001). The results are mixed regarding completion rates, passing rates, and course satisfaction with the majority of findings favoring classroom-based and blended learning courses (Bernard, Abrami, Lou, Borokhovski, 2004a; Carr, 2000; Saba, 2000b). Diaz (2000), Saba (2000a), and Ungerleider & Burns (2003) rated the quality of distance education research as poor and Bernard et al. (2004a) raised the following issues: "(a) lack of experimental control, (b) lack of

procedures for randomly selecting research participants, (c) lack of random assignment of participants to treatments, (d) poorly designed dependent measures that lack reliability and validity, and (e) failure to account for a variety of variables related to the attitudes of students" (p. 176). They also suggested that future research involve comparisons within distance education courses and not between distance education and some other form of instruction.

The independent study context of this study provides a unique opportunity to conduct a randomized controlled experiment because students could be randomly assigned to treatment groups once they enroll in the course. Campbell and Stanley (1963) described the experiment as:

> the only means for settling disputes regarding educational practice, as the only way of verifying educational improvements, and as the only way of establishing a cumulative tradition in which improvements can be introduced without the danger of a faddish discard of old wisdom in favor of inferior novelties. (p. 2)

In answer to Bernard et al. (2004) suggestion for comparative studies within distance education courses, the proposed study compares different types and levels of student-teacher interaction within an online distance education course. To improve student performance, course completion, and course satisfaction, this research focuses on virtual teacher-student dialogue as manifested by periodic email messages based on student performance and periodic invitations to participate in an online discussion board.

Frankola (2001) listed three reasons why online learners drop out in corporate settings: lack of management oversight, lack of motivation, and lack of student support. His proposed solutions to decrease dropout rates that are relevant to this research project are: create discussion groups; use software to track student progress and email non-participating students or potential course dropouts; provide access to tutors through email, phone or threaded discussions; and

provide an online database for answers to most frequently asked questions. In 1987, Chickering and Gamson offered seven principles for good practice in undergraduate education and the first principle was to encourage contacts between students and faculty in face-to-face instruction. In 2001, Graham, Cagiltay, Lim, Craner, and Duffy applied these seven principles to evaluate online courses and recommended that "instructors should provide clear guidelines for interaction with students" (p. 2) particularly when responding to email messages.

According to Thurmond and Wambach (2004), in web-based courses, teacher-student interaction is solely transmitted by electronic means, such as chat discussions or email communications. Aragon (2003) suggested the following strategies for creating social presence within social environments: develop a welcome video, contribute to discussion boards, promptly answer emails, provide frequent feedback, and use humor and emoticons. Lemak et al. (2005) and Lehman, Kauffman, White, Horn, and Bruning (2001) found that the use of email enhanced the educational experience. Simpson (2004) also found that motivational contact by offering encouragement through emails had a positive influence on course completion. He indicated that such contact did not need to be personalized to be beneficial and further suggested that such contacts across the period of study be brief, informal, and appropriate. Aragon and Johnson (2008) recommended that "all courses should have a communication system embedded within the class, whether it is email, web-boards, or chat rooms" (p. 155). Roblyer (2006) also pointed out that policies and practices that required teachers to track student progress and proactively reach out to inactive students via emails are best practices. However, these policies and practices were not based on formal research and were not linked to improved academic performance. This research aims to fill these gaps. Wheeler (2007) found that email facilitated the highest level of immediacy of dialogue for most students and that the effects of transactional distance could be

better analyzed if two sub-variables of dialogue are recognized: social presence (the perception of connectedness between students and their teachers or tutors) and immediacy (the temporal effects of dialogue). However, he did not relate reduced transactional distance specifically to increased student performance or satisfaction. Hawkins, Graham, Sudweeks, and Barbour (2013) recommended that teachers take proactive measures to reach out to students regardless of their progress in the course. The increased interaction may be enough to move students from the non-completion status to completion status. Simpson (2004) suggested that "to achieve effective retention to the end of a course, it will probably be necessary to develop a systematic program of carefully timed interventions covering the whole course" (p. 93).

Based on these research findings and recommendations, one of the chosen interventions in this experiment is a regular email feedback regarding student progress in the course, encouragement to those who either have not completed any work in a given period of time or achieved low scores, and congratulatory messages to those who are on track to pass the course. These emails are treated as a resource which supports educational dialogue. The other chosen intervention is a recurring invitation to participate in a discussion board initiated by teaching assistants. Participation in the discussion is not required or graded but encouraged with the information that discussion board topics are associated with the essay portion of the exams and writing assignments. The reason for this is that some students seek to finish an independent study course in a short a time as possible and participation might hamper their progress in the course. Picciano (2002) also warned that:

> While much of the research relates student satisfaction and performance to the active
> participation in online course activities, faculty teaching these courses face a small
> dilemma in establishing requirements for interacting online because some students may

not need to participate actively in the course to do well on a test or some other

performance measure. (p. 23)

In addition, the format of this independent study course precludes in-time discussion

among students because class members are in different stages of course completion. Tudor

(2006) aimed to show that online statistics courses can include instructor interaction that would

satisfy students. Her students were enrolled in an entry level master's course where she provided

exam feedback, organized her students in small groups, sent regular emails and announcements.

Posted comments in the small group discussions were graded and she trained her teaching

assistants in grading. She claimed that interesting and controversial topics with detailed

instructions and specific questions were keys to having good discussions. She reported that

"Some students found the discussion to be awkward because the students lived in different time

zones or because the speed of their internet connection was too slow. It appears that the

effectiveness of online discussion in a statistics class is still debatable" (p. 4).

Characteristics of Successful Students in Online Distance Education Courses

Demographic Characteristics

Previous studies have sought to account for the reasons why online distance education

students have low completion rates by classifying students according to their characteristics in

order to predict those who are more likely to drop out (Aragon & Johnson, 2008; Diaz, 2002;

Morgan & Tam, 1999). Bernard et al. (2004b) suggested that future researchers study student

readiness for online distance education learning by determining "which existing characteristics,

skills, behaviors, and attitudes contribute to achievement and satisfaction" (p. 192). Belawati

(1998) found that non-completion was related to student's age, gender, previous education,

employment status, and course workload. Diaz (2002) listed eight factors that influence attrition

rates in online distance education: demographics, quality of class, discipline, educational

preparation, motivational and persistence attributes, socio-economic factors, teacher experience, and online orientation process. He also demonstrated the positive relationship between high school grade point average (GPA) and course completion. Aragon and Johnson (2008) investigated the factors that influence completion rates in community college online courses. They found that previous GPA, as measured at entry at the beginning of the semester of data collection, was significantly different for completers and non-completers in online courses. Students with lower GPAs were more likely to drop their online courses (Hawkins, 2013; Roblyer, Davis, Mills, Marshall, & Pape, 2008; Parker, 2003; Dupin-Bryan, 2004). Bean and Metzner (1985) identified four factors that affect persistence. One of them was background and defining variables such as age, educational goals, ethnicity, and prior GPA. Accordingly, high school GPA is used as a covariate of interest in this study.

Hawkins et al. (2013) discussed several factors that might influence student performance in postsecondary online learning. Among them were gender, age, prior academic success, motivation level, and independent learning styles. She found that gender and age were not significant predictors of completion rates but past performance, in terms of grade point average, was a strong predictor of success. In addition, student's locus of control, motivational level, and independent learning styles were predictive of successful online learning. However, Ross and Powell (1990) reported that females tend to be more successful in online courses than males. Fredericksen et al. (2000) also found that women had higher levels of perceived learning than men in online learning. Rovai (2001) found similar gender-related differences in an online course. Elmore & Vasu (1986) found that their female students performed better in their statistics classes. Vella, Turesky, and Hebert (2016) reported that the following student attributes positively predicted "both higher course grades and successful completion in online

courses: older age, female gender, higher GPA, graduate student status, and part-time academic load" (p. 596). In addition, some studies have indicated that student's previous mathematics background is also related to success in statistics classes (Elmore, Lewis, & Bay, 1993; Presley & Huberty, 1988). Hence, gender and Math ACT score, as a measure of Math background and aptitude, are added as control variables in the study.

Learner Autonomy

Tucker (2000) characterized successful distance students as autonomous and independent learners. Moore (1993) initially defined learner autonomy in terms of learners being able to determine learning goals and assessment methods. He theorized that learners with high autonomy prefer less dialogue and less structure. Learners with low autonomy will depend more on the teacher and favor more dialogue and more structure. In this study, the only aspects of the course that learners can control are the time, place, and pace of study. As such, Moore's definition will be restated in terms of independent learning or self-regulated learning where students take responsibility for their learning. Kerr, Rynearson, and Kerr (2006) reported that "the subscale that yielded the most frequent, consistent, and useful results was independent learning… which consists of items that assess one's ability to manage time, balance multiple tasks, and set goals" (p. 101). They concluded that "the successful online student is self-directed and independent" (p. 102). In his later writings, Moore combined the terms independence, autonomy and self-directed learning into one concept (Garrison, 2003). He asserted that self-directed learning is the key and defining characteristic of learning associated with distance education or independent study.

Learner autonomy has been long considered an essential attribute of successful online learners. Varvel (2001) found that successful online students tended to be self-disciplined and motivated with strong time-management skills. Rovai (2003) claimed that "learner autonomy,

that is, the concept of independence and self-direction, has been a hallmark of adult education and an assumed characteristic of the nontraditional students enrolled in distance education programs" (p. 12).

Based on the literature review of the characteristics of successful students in online distance education courses, the control variables that are of interest in this experiment are: (a) age, (b) gender, (c) high school GPA, (d) math ACT score, and (e) level of learner autonomy.

Characteristics of Successful Students in Introductory Statistics Courses

A few online distance education scholars have suggested doing more research on specific disciplines (Kerr et al., 2006; Song & Hill, 2007). The specific subject matter of this study is introductory statistics courses. Statistics education is a relatively new and emerging discipline that started in the 1980s (Garfield & Ben-Zvi, 2007) which focuses on the teaching and learning of statistics. There have been many case studies examining student dropout and persistence in beginning statistics courses. Terry (2001) cited in Angelino, Williams, and Natvig (2007), for example, found that more technical classes such as business statistics and finance courses had higher attrition in their distance education versions, whereas other business courses had comparable attrition rates. Other studies in statistics education have shown that attitude towards statistics is one of the best predictors of achievement in research methodology and statistics courses (Finney & Schraw, 2003; Garfield & Ben-Zvi, 2007; Kohli, Peng, & Mittal, 2011; Onwuegbuzie & Wilson, 2003). Gal, Ginsburg, and Schau (1997) reported that students' attitude towards statistics affect persistence and achievement. They also claimed that "there is almost no research on the nature of statistics attitudes and beliefs, on their relationship with achievement and persistence, and on attitude patterns in different types of learners (e.g., group differences among males and females or minority and non-minority students)" (p. 48). In 2012, Nolan,

Beran, and Hecker reported that "students with positive attitudes toward Statistics are likely to show strong academic performance in Statistics courses." (p. 103).

Gal and Ginsburg (1994) suggested that "students' feelings about statistics education, and the effects of these feelings on resulting learning, knowledge and further interest in statistics, should occupy a more central role in the minds of statistics educators" (Pearl et al., 2012, p.8). Ramirez, Schau, and Emmioğlu (2012) created a conceptual model with three constructs that are believed to be related to statistics course outcomes: student characteristics, previous achievement, and attitudes toward statistics. Furthermore, Emmioğlu and Capa-Aydin (2012) used meta-analysis to show that the relationships among attitudes and course achievement was positive. The most common measures of attitude toward statistics comprise the subscales of cognitive competence or self-efficacy and value or usefulness of the subject matter. The next two sub-sections will discuss these two constructs.

Self-efficacy

Self-efficacy refers to a person's belief or confidence in his or her own ability to perform certain tasks effectively (Yusuf, 2011). Research in educational psychology has shown that motivational factors like expectancy beliefs or confidence in learning are related to success in education (Bandura, 1986; Wigfield & Eccles, 1992). Zimmerman (2000) reported on a study by Pajares and Miller in 1994 that showed "Math self-efficacy was more predictive of problem solving than was math self-concept or, for that matter, perceived usefulness of mathematics, prior experience with mathematics, or gender" (p. 85). Del Vecchio (1994) also showed a relationship between cognitive competence and persistence: students who reported more confidence in their abilities to do statistics were more likely to complete their course with a passing grade. Schutz, Drogosz, White, and Distefano (1998) demonstrated that confidence about learning statistics was significantly correlated with student performance. Finney and

Schraw (2003) considered other factors that might affect performance like perceived competence or self-efficacy. They developed measures of current statistics self-efficacy (CSSE) and self-efficacy to learn statistics (SELS) to test if these constructs were related to statistics performance. They found that these two measures were related positively to attitudes towards statistics and overall course performance. Zimmerman (2000) indicated that "two decades of research have clearly established the validity of self-efficacy as a predictor of students' motivation and learning" (p. 89). The specific measure of self-efficacy that is used in the study is confidence in learning statistics.

Opinion on Worth of Subject Matter

Morgan and Tam (1999), reported that some of the reasons given by students who dropped out of distance education courses were that the subject matter lacks personal interest and was not relevant to the students' work. Summers, Waigandt and Whittaker (2005) claimed that "many students choose to use surface level strategies to learn the material because they do not perceive statistics knowledge as useful or meaningful" (p. 237). Singer and Willet (1990) and Thompson (1994) sought to improve learning in college statistics classes by enhancing the relevance of the subject. However, Schutz et al. (1998) reported that the value statistics attitude scale which measures a student's opinion on the "usefulness, relevance, and worth of statistics in personal and professional life" was not significantly correlated with student performance" (p.294). Lim and Kim (2003) further identified six elements of learning motivation, three of which were perceived relevance or usefulness of subject matter, self-competence or confidence in achieving a certain task, and learner control. Based on these research results, the specific attitude that will be addressed by this study is opinion on the usefulness of statistics.

Existing Measures of Constructs of Interest

Learner Autonomy

A preliminary search revealed that there is no single consensual definition of the term "autonomous learning" and its related constructs of "independent learning" and "self-directed learning" (Macaskill & Taylor, 2010). Murase (2007) believed that the operationalization of learner autonomy is a difficult task because it is widely considered as multidimensional. It is also problematic and has not been applied to an online distance education statistics course. Holec (1981) described it as the ability to take charge of one's learning. A universal definition of autonomous learning or learner autonomy has not been agreed upon but the following characteristics are considered essential by Tassinari (2012):

- Metacapacity of the learners to take control of their learning process to different extents and in different ways according to the learning situation.

- A complex construct with the following essential components: cognitive and metacognitive, affective and motivational, action-oriented, and social.

- Capacity of the learner to activate an interaction and balance among these components in different learning contexts and situations.

There has also been a lack of short, valid, and reliable measure of this attribute. The most commonly used measure of learning autonomy is Guglielmino's Self-directed Learning Readiness Scale (1977) consisting of 58 items but questions have been raised about its construct validity (Straka & Hinz, 1996; Fisher, King, & Tague, 2001). This scale has been the subject of various construct validation studies which recommended its discontinuance (Candy, 1991; Field, 1989; Straka & Hinz, 1996). Doherty (2000) and Pachnowski and Jurczyk (2000) used SDLRS and both studies found that self-directedness was not a strong indicator of academic success in online courses. To determine what student characteristics are important in online learning, Kerr

et al. (2006) created the Test of Online Learning Success (TOOLS) scale and one of the subscales used was Independent Learning which consisted of 10 items that "assess one's ability to manage time, balance multiple tasks, set goals, and one's disposition regarding self-discipline, self-motivation, and personal responsibility" (p. 101). They reported that the four most important characteristics for predicting online student success were reading and writing skills, independent learning, motivation, and computer literacy. They clarified that "autonomy is one of the foundational dimensions of independent learning and the one that considers the learner's point of view of the transaction" (p. 101). Macaskill and Taylor (2010), offered an operational definition of learning autonomy as learners who can take responsibility for their own learning, are motivated to learn, gain enjoyment from their learning, are open-minded, manage their time well, plan effectively and plan tasks carefully, meet deadlines, are happy to work on their own, display perseverance when encountering difficulties, and are low in procrastination when it comes to their work. They developed a 12-item scale that was shown to be psychometrically sound but its predictive power has not been tested. The proposed study tests the predictive power of the scale that was developed: learner autonomy is used as a predictor variable in an analysis of covariance with student achievement and satisfaction as response variables. It also defines learner autonomy as the extent in which the learner takes responsibility for their own learning as manifested by planning one's own learning and being intrinsically motivated.

Attitude Towards Statistics

Past research on attitudes in statistics education showed a small to moderate relationship between attitudes (using the Attitudes towards Statistics Scale or ATS) and achievement in statistics at the post-secondary level (Green, 1994; Waters, Martelli, Zakrajsek, & Popovich, 1988; Wise,1985; Woehlke, 1991). Schau, Stevens, Dauphinee, and Del Vecchio (1995) reported similar relationships between course grade and pre-and post-course attitude

scores on affect, cognitive competence, and value scales (using the Survey of Attitudes toward Statistics or SATS). However, Gal et al. (1997) suggested that "Continued efforts to improve and systematize alternative item formats and examine their reliability and validity are needed to improve the quality and conceptual coverage of the measures currently available" (p. 48).

Multiple instruments in the form of surveys measuring students' attitude toward Statistics have been developed, starting as early as the 1950's (Bendig & Hughes, 1954). According to Nolan et al. (2012):

> Although each of these surveys claims to measure student's attitude towards statistics, the dimensionality, items, and results vary among surveys, suggesting that this construct is not yet clearly defined. Currently, a summary and comparison of the validity and reliability evidence for these various interpretations is absent from the literature, making it difficult for statistics educators to make evidence-based decisions when selecting a survey or deciding where additional research and development are needed. (p.103)

Nolan et al.'s 2012 paper sought to identify all peer-reviewed and non-peer reviewed surveys that attempted to assess student's attitude towards statistics and evaluated their construct and internal consistencies. The authors looked at 532 citations from relevant electronic databases and reviewed 78 of the citations. From this review, 35 citations were included in the final analysis. Fifteen surveys were identified but only four scales had an accumulation of validity and reliability evidence. Table 18 compares these four scales.

Table 18

Comparison of Most Commonly Used Scales Measuring Attitude Toward Statistics

Scale	# of Likert-type points	Date created	# of items	Number of and dimensions measured
Statistics Attitude Scale (SAS)	5-point	1980	34	one
Attitudes Toward Statistics Scale (ATS)	5-point	1985	29	two (field and course)
Survey of Attitudes Toward Statistics (SATS-28)	7-point	1995	28	Four (Affect, Cognitive competence, Value, and Difficulty)
Survey of Attitudes Toward Statistics (SATS-36)	7-point	2003	36	Six(Affect, Cognitive competence, Value, Difficulty, Interest, and Effort)

From the 15 surveys that were identified and evaluated by Nolan et al., three common elements emerged: affect, perceived ability to learn and/or understand statistics, and perceived value of statistics. For future research, they recommended

the need for additional, peer-reviewed validation research and improved consistency in reporting reliability evidence. Although four instruments were identified that had been used in multiple validation studies, none of the items and scores from the underlying dimensions had accumulated a large amount of content, substantive, structural or external validity, and none, specifically possessed evidence of all four. (p. 120)

Van Hoof, Kuppens, Sotos, Verschaffel, and Onghena (2011) investigated the six-factor structure of SATS-36, the most widely used questionnaire, and concluded that it can be improved by removing some poorly functioning items and that either the six subscales could be used or

three of them (Affect, Cognitive Competence, and Difficulty) can be combined into one subscale without losing much information.

Even as recently as 2012, the American Statistical Association (ASA) published an education research report which identified four broad priorities pertaining to affective constructs or students' attitudes. Their first priority was developing accurate measurement of affective constructs within the context of statistics" (Pearl et al., 2012). This study aimed to develop reliable and abbreviated scales measuring perceived ability to learn statistics and the perceived usefulness of statistics.

In summary, numerous studies have investigated the factors that impact student persistence, student achievement, and student satisfaction in distance education and online learning. Using Moore's transactional distance theory, Garrison's community of inquiry, and other theories of instruction (Anderson, 2008; Caspi & Gorsky, 2006), these studies have shown the importance of teacher-student dialogue in reducing transactional distance which in turn leads to greater student performance and student satisfaction. Some of these studies have proposed specific interventions to increase teacher-student interaction. While many possible solutions have been proposed, few have been tested empirically. The few evidence-based studies showed mixed results and were not in complete agreement. This research project used some of the proposed solutions that were controllable and achievable in the context of a relatively large online independent study course. Specifically, this research aimed to enhance instructional dialogue by using regular email feedback on student progress and reminders to students who are lagging behind in course work, and utilizing statistics-related discussion boards monitored and responded to by tutors. To account for other variables that may affect the outcome of the study, age, gender, previous student achievement, level of learner autonomy, and attitude toward

statistics were used as control variables. Another goal of this study was to provide future statistics education researchers with three abbreviated scales of learner autonomy, opinion on the usefulness of statistics, and confidence in learning statistics. The research findings will hopefully benefit both students and instructors as the latter design instruction and incorporate dialogue in the course to engage their students.

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APPENDIX B

Email Templates for Section M001

For those who have completed at least three credit quizzes in a week and obtained at least 85% in each quiz:

Congratulations!! You have completed at least three credit quizzes the past week and have scored at least 85% in each quiz. You're on track to complete the class in twelve months' time and very likely to pass the class.

We wish you the best,
The Stat 121 team of Prof. Nielsen and Stat tutors

For those who have not submitted any quiz for two weeks:

We hope you are doing well. We have not seen any quiz activity from you in the last two weeks. We are concerned that you may be falling behind in your course completion. Please schedule a time and place where you can work on the reading assignments, do the practice quizzes and complete the credit quizzes.

We wish you the best,
The Stat 121 team of Prof. Nielsen and Stat tutors

For those who have been getting less than 65% on their last six quizzes:

We hope you are doing well. We are concerned that you may be falling behind in your course completion. Please schedule a time and place where you can work on the reading assignments, do the practice quizzes and complete the credit quizzes. Also, please contact the Stat tutor for help with the quizzes.

We wish you the best,
The Stat 121 team of Professor Nielsen and Stat tutors

APPENDIX C

Discussion Forum Questions

Announcement (*Post at the top of the Moodle course*):

We hope you're enjoying and learning a lot in this course. We would like you to join our Discussion forum by responding to the questions that will be posted in some lessons. Your comments will be responded to by one of the Stat tutors. You are also welcome to post your own questions that are relevant to the topic posted and respond to other student's comments. These discussion questions might help you in the essay portion of the exams and the writing assignments.

1. Getting to Know You
   - Share something unique about you
   - What is your major?
   - What are your course expectations?
   - You can also share cartoons, studies and You Tube videos about Statistics ☺
   (*Post after lesson 1*)

2. Is it true that variation is everywhere? Give examples.
   (*Post after lesson 3*)

3. In data collection, why is random selection very important in observational studies? Why is random assignment of subjects to treatments critical in controlled experiments? Explain and give examples.
   (*Post after lesson 6*)

4. In quantitative data analysis, why should we always plot our data first before we make any numerical calculations?
   (*Post after lesson 11*)

5. Why does association not imply causation? Give examples.
   (*Post after lesson 15*)

6. Why should we check conditions before we calculate a test statistic or a confidence interval?
   (*Post after lesson 25*)

7. What does a test statistic measure?
   (*Post after lesson 27*)

8. Why do we reject the null hypothesis when the P-value is small?
   (*Post after lesson 29*)

9. When given a bivariate data set, how will you determine whether you are going to do chi-square analysis, regression, or analysis of variance?
   (*Post after lesson 37*)

APPENDIX D

Post-Course Satisfaction Survey

Please respond to the following items regarding this course:

1. The course was what I expected.
   - Strongly disagree
   - Disagree
   - Somewhat disagree
   - Somewhat agree
   - Agree
   - Strongly agree

2. How often did you request assistance from the Stat tutor?
   - 2 or more times a week
   - Once a week
   - 2-3 times a month
   - Once a month
   - Less than once a month
   - Never

3. How helpful were Stat tutors in answering your questions?
   - All were very helpful
   - All were somewhat helpful
   - Some were helpful and some were not
   - All were not very helpful
   - None were helpful
   - Never asked for Stat tutor help

4. What aspect of the Moodle quizzes did you find most helpful?
   - The ability to submit the quizzes online (as opposed to turning in a paper submission)
   - The format of the quizzes (the questions were all on one page)
   - The printed graphs and tables
   - The ability to save my answers and finish the quizzes at a later time
   - The ability to receive immediate feedback on the quizzes

5. Navigation in the Moodle website was easy and intuitive.
   - Strongly disagree
   - Disagree
   - Somewhat disagree
   - Somewhat agree
   - Agree
   - Strongly agree

6. Regardless of my grade in the course, I was satisfied with the Moodle course website overall.
   - Strongly disagree
   - Disagree
   - Somewhat disagree
   - Somewhat agree
   - Agree
   - Strongly agree

7. What aspect of StatsPortal did you find most helpful?
   - The embedded hyperlinks on the eBook
   - The ability to highlight important passages on the eBook
   - The instant ability to access glossary terms on the eBook pages
   - The Stat tutor videos
   - Personalized study plans
   - I didn't purchase a StatsPotal access code

8. Regardless of my grade in the course, I felt StatsPortal helped me understand the subject matter.
   - Strongly disagree
   - Disagree
   - Somewhat disagree
   - Somewhat agree
   - Agree
   - Strongly agree
   - Did not use StatsPortal

9. Navigation in StatsPortal was easy and intuitive.
   - Strongly disagree
   - Disagree
   - Somewhat disagree
   - Somewhat agree
   - Agree
   - Strongly agree
   - Did not use StatsPortal

10. Regardless of my grade in the course, I was satisfied with StatsPortal overall.
    - Strongly disagree
    - Disagree
    - Somewhat disagree
    - Somewhat agree
    - Agree
    - Strongly agree
    - Did not use StatsPortal

11. Which of the following did you do in preparation for exams? Check all that apply.
- Read material in textbook or eBook
- Took the practice exams
- Studied the jeopardy questions
- Worked with the Stat tutor
- Studied the glossary terms
- Watched StatTutor videos on StatsPortal
- Reviewed practice and credit quizzes
- Did not prepare for exams

12. Overall, I am very satisfied with the Stat 121 Independent Study course.
- Strongly disagree
- Disagree
- Somewhat disagree
- Somewhat agree
- Agree
- Strongly agree

APPENDIX E

Pre-Course Survey Questions

Please respond to each of the following items regarding this course.

What is your main reason for taking this course?
- To complete a degree
- Can take it in 12 months
- Employed full time
- Prefer to learn at my own pace
- Prefer online learning
- Others _____

Determine to what extent you agree or disagree with the following statements:

The study of Statistics will be very useful in my daily life.
- Strongly disagree
- Disagree
- Somewhat disagree
- Somewhat agree
- Agree
- Strongly agree

The study of Statistics will be very useful in my work.
- Strongly disagree
- Disagree
- Somewhat disagree
- Somewhat agree
- Agree
- Strongly agree

I am looking forward to learning Statistics.
- Strongly disagree
- Disagree
- Somewhat disagree
- Somewhat agree
- Agree
- Strongly agree

I feel confident in my ability to learn Statistics.
- Strongly disagree
- Disagree
- Somewhat disagree
- Somewhat agree
- Agree
- Strongly agree

I feel comfortable doing Math story problems.
- Strongly disagree
- Disagree
- Somewhat disagree
- Somewhat agree
- Agree
- Strongly agree

I will enjoy completing this online Statistics course.
- Strongly disagree
- Disagree
- Somewhat disagree
- Somewhat agree
- Agree
- Strongly agree

I have no desire to avoid Stat courses.
- Strongly disagree
- Disagree
- Somewhat disagree
- Somewhat agree
- Agree
- Strongly agree

Statistics is not a difficult subject.
- Strongly disagree
- Disagree
- Somewhat disagree
- Somewhat agree
- Agree
- Strongly agree

I do very well learning on my own.
- Strongly disagree
- Disagree
- Somewhat disagree
- Somewhat agree
- Agree
- Strongly agree

I can keep to a schedule.
- Strongly disagree
- Disagree
- Somewhat disagree
- Somewhat agree
- Agree
- Strongly agree

I plan to study well for this online Statistics class.
- Strongly disagree
- Disagree
- Somewhat disagree
- Somewhat agree
- Agree
- Strongly agree

I will prepare well for each of the midterm exams.
- Strongly disagree
- Disagree
- Somewhat disagree
- Somewhat agree
- Agree
- Strongly agree

I don't need external rewards in order to feel motivated.
- Strongly disagree
- Disagree
- Somewhat disagree
- Somewhat agree
- Agree
- Strongly agree

APPENDIX F

IRB Approval and Implied Consent Form

Implied Consent to be a Research Subject

Introduction

This research study is being conducted by **P. Lynne Nielsen and Del T. Scott** at Brigham Young University to investigate the impact of different types and levels of instructional dialogue on Stat 121 completion rates, passing rates and student satisfaction. You were invited to participate because you have registered in the course.

Procedures

If you agree to participate in this research study, the following will occur:

- you will be asked to complete a 5-minute pre-course survey
- you will be randomly assigned to one of four sections with different types and levels of instructional dialogue
- you will be asked to complete a 10-minute post-course survey
- you may also be asked to participate in an online discussion forum

The researchers will access the results of these surveys, exam and quiz scores, and demographic information available in the Independent Study database and the Statistics department's Moodle course website.

Students who do not wish to participate will still need to complete quizzes and exams to receive a grade but this information will not be used for research purposes.

Risks/Discomforts

There is minimal risk for participation in this study. Possible sources of discomfort may be being asked about your attitude towards Statistics and the reason(s) you enrolled in the course.

Benefits

There are no direct benefits to you. However, this research might:

- help future Statistics 121 Independent Study students be more successful in the course,
- inform BYU Independent Study of what online course features to add to their course offerings to promote instructional dialogue and student success, and
- add to distance education theory, research, and practice to improve student performance and satisfaction.

Confidentiality

The only identifying information the researchers will collect from you is your netID. This information will be needed to merge the BYU Independent Study Stat 121 and the department of Statistics Moodle databases. As soon as these databases are merged and the data file verified for accuracy and completeness, netIDs will be deleted from the data file prior to statistical analysis. The research data will be kept in a password protected computer owned by the department of Statistics and only the researchers will have access to the data. At the conclusion of the study, the data will be archived in the researcher's password protected computer on campus.

Participation

Participation in this research study is voluntary. You have the right to withdraw at any time or refuse to participate entirely without jeopardy to your class status, grade, or standing with the university. If you decide to withdraw from the research study, email the researcher at nielsen@stat.byu.edu with your

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BYU	07/10/13 Approved	07/09/14 Expires

request and your netID so all your quiz and exam scores can be transferred to the section for non-participants. To earn a course grade, you need to complete all the requirements stated in the course syllabus.

Questions about the Research
If you have questions regarding this study, you may contact Prof. Nielsen at nielsen@stat.byu.edu or Dr. Del Scott at scottd@byu.edu, for further information.

Questions about Your Rights as Research Participants
If you have questions regarding your rights as a research participant contact IRB Administrator at (801) 422-1461; A-285 ASB, Brigham Young University, Provo, UT 84602; irb@byu.edu.

Statement of Implied Consent
Your checking of the item labeled [1] below implies your consent to participate. Thank you!

[1] I would like to participate in this study   [2] I do not want to participate in this study