Developing and Testing a Model to Understand Relationships between e-Learning Outcomes and Human Factors

Sean B. Eom[1] and Nicholas J. Ashill[2]
[1]*Department of Accounting, Southeast Missouri State University, 1 University Plaza, Cape Girardeau, U.S.A.*
[2]*Department of Marketing, American University of Sharjah, Sharjah, U.A.E.*

Keywords: e-Learning Outcomes, Human Factors, Student Satisfaction, Interaction.

Abstract: This study applies partial least squares (PLS) to examine the effects of interactions and instructor feedback and facilitation on the students' satisfaction and their perceived learning outcomes in the context of university online courses. Independent variables included in the study are course structure, self-motivation, learning style, and interaction. A total of 397 valid unduplicated responses from students who have completed at least one online course at a university in the Midwest U.S. are used to examine the structural model. Four of the five antecedent constructs hypothesized to directly affect student/instructor interaction are significant. This research makes a critical contribution in e-learning empirical research by identifying two critical human factors that make e-learning a superior mode of instruction.

1 INTRODUCTION

According to a comprehensive online and blended learning literature review (Arbaugh et al., 2009), e-learning empirical researchers have accumulated important findings in regard to potential predictors of e-learning outcomes, control variables, and criterion variables. This review identified two most common research streams: first, a comparison of learning outcomes between face-to-face and e-learning course delivery modes; second, research which examined potential predictors of e-learning outcomes. Previous empirical studies in this area of prediction of e-learning outcomes can be broadly classified into (1) conceptual frameworks that identify factors that affect e-learning outcomes and learner satisfaction, (2) empirical studies that examine a subset of factors on learning outcomes (e.g., effects of e-learner characteristics such as gender, age and e-learning experience), and (3) empirical studies examining factors and their effects on e-learning outcomes and (4) empirical studies examining factors that make e-learning a superior mode of instruction. Many research models that identify the predictors of e-learning outcomes are built on the conceptual frameworks of Piccoli et al., (2001) and Peltier et al., (2003). The former identifies human and design factors as antecedents of learning effectiveness. Human factors are concerned with students and instructors, while design factors characterize such variables as technology, learner control, course content, and interaction. The conceptual framework of online education proposed by Peltier et al., (2003) consists of instructor support and mentoring, instructor-to-student interaction, student-to-student interaction, course structure, course content, and information delivery technology.

Empirical studies however, report conflicting findings. Eom et al., (2006) for example, examined the determinants of students' satisfaction and their perceived learning outcomes in the context of university online courses. Independent variables included in this study were course structure, instructor feedback, self-motivation, learning style, interaction, and instructor facilitation as potential determinants of online learning. The results indicated that all of the antecedent variables significantly affect students' satisfaction. Of the six antecedent variables hypothesized to affect the perceived learning outcomes, only instructor feedback and learning style were significant. Although this study represents an important milestone in e-learning empirical research by fundamentally shifting the focus of e-learning empirical studies from simply identifying the predictors of e-learning outcomes to identifying a

B. Eom S. and J. Ashill N..
Developing and Testing a Model to Understand Relationships between e-Learning Outcomes and Human Factors.
DOI: 10.5220/0004437803610370
In *Proceedings of the 15th International Conference on Enterprise Information Systems* (ICEIS-2013), pages 361-370
ISBN: 978-989-8565-60-0
Copyright © 2013 SCITEPRESS (Science and Technology Publications, Lda.)

subset of critical success factors that makes learning outcomes surpass those provided in classroom-based settings, some of the study's findings run contrary to other studies. For example, Eom et al. (2006) found no support for a positive relationship between interaction and perceived learning outcomes, a finding that runs contrary to LaPointe and Gunawardena (2004).

In the current study, we advance current research by examining relationships between e-learning outcomes and human factors, especially human interactions, in university online education using e-learning systems. Specifically, our conceptual model examines the human interaction construct and we place this construct as a mediating variable between learning outcomes and other three constructs (course structure, motivation, and learning styles). Using the extant literature, we begin by introducing and discussing the research model illustrating factors affecting e-learning systems outcomes and e-learner satisfaction. We follow this with a description of the cross-sectional survey that was used to collect data and the results from structural equation modeling (SEM) analysis using PLS-Graph. PLS-based SEM yields robust results despite that it does not have measurement, distributional, or sample size assumptions. In the final section, we summarize and conclude with the implications of the results for e-learning.

2 RESEARCH MODEL

Figure 1 summarizes research questions we attempt to answer. There are three antecedents (course structure, students' motivation, and students' learning styles) of interactions. The impact of three constructs on learning outcomes is mediated by interaction.

2.1 Antecedents of Interaction

e-Learning systems aim to maximize learning outcomes using learning management systems. In doing so, understanding widely accepted learning theories is prerequisite to apply these learning management systems and technologies, because it defines different roles the instructor and students have to play in the learning process and the roles of dynamic interactions among human subsystems (students, the instructor), technology, and contents in the learning process. The most widespread learning paradigms are the behaviorist paradigm of learning (behaviorism), the constructive paradigm of learning (constructivism) and the cognitive paradigm of learning (an extension of constructivism). With increasing adoption of e-learning, constructivism has become the dominant learning theory. Constructivism assumes that individuals learn better when they control the pace of learning. Therefore, the instructor supports learner-centered active learning. Under the cooperative model of learning (collaboratism), students learn as individual students and verify, solidify, construct and improve shared understanding of their mental models. It is necessary for students to interact with other students and the instructor in the form of active forum discussions, private e-mails, teleconferencing and group project completion. The interaction and active participation enable students to construct and share the new knowledge. In this learning process, student involvement is critical to learning and the instructor becomes a discussion leader. The socioculturism model necessitates empowering students with freedom and responsibilities since learning is individualistic (Leidner and Jarvenpaa, 1995). Moreover, e-learning places greater emphasis on the constructive paradigm of learning (constructivism) and the cognitive paradigm of learning (an extension of constructivism). Consequently, the role of interaction among students and between students and the instructor in the e-learning process has become critical.

The design dimension in Piccoli et al., (2001) includes a wide range of constructs that affect effectiveness of e-learning systems such as technology, learner control, learning model, course contents and structure, and interaction. Among the many frameworks/taxonomies of interaction (Northrup, 2002), this research adopts Moore's (1989) communication framework which classified engagement in learning through (a) interaction between participants and learning materials, (b) interaction between participants and tutors/experts, and (c) interactions among participants. These three forms of interaction in online courses are recognized as important and critical constructs determining the performance of web-based course quality.

The community of inquiry model is another useful framework that explains the roles of interaction to achieve higher learning outcomes and learner satisfaction. The community of inquiry framework emphasizes the creation of an effective online learning community that enhances and supports learning and learner satisfaction (Akyol and Garrison, 2011). The essence of the effective online learning community is the creation of cognitive presence, which is a condition/learning environment

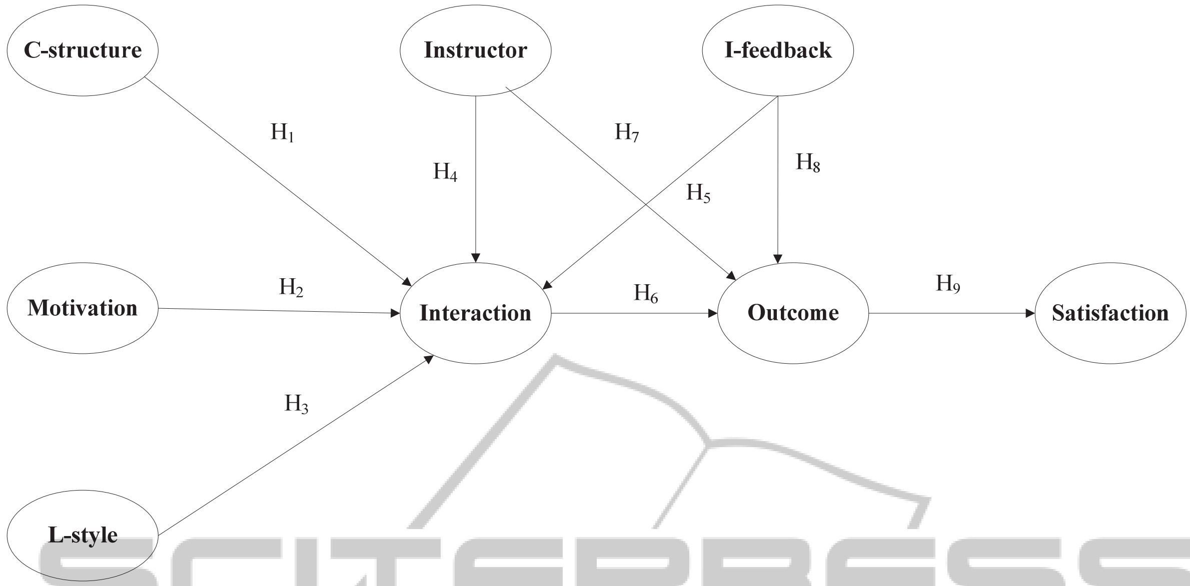

Figure 1: Research model.

that facilitates higher-order thinking and deep and meaningful learning (Garrison and Anderson, 2003). Cognitive presence in the e-learning process facilitates e-learners to freely exchange ideas and information and connect ideas to construct new knowledge. In doing so, interactions with students and the instructor becomes a necessary ingredient in the learning process. The next element of the community of inquiry model is social presence. According to Garrison (Garrison, 2009, p.352), social presence is defined as "the ability of participants to identify with community (e.g., course of study), communicate purposefully in a trusting environment, and develop interpersonal relationships by way of projecting their individual personalities."

2.1.1 Course Structure

Course structure is seen as a crucial variable that affects the success of distance education along interaction. According to Moore (1991, p.3), the course structure "expresses the rigidity or flexibility of the program's educational objectives, teaching strategies, and evaluation methods" and the course structure describes "the extent to which an education program can accommodate or be responsive to each learner's individual needs."

Course structure has two structural elements - course objectives/expectation and course infrastructure. Course objectives/expectation are specified in the course syllabus including expected class participation in the form of online conferencing systems and group project assignments. These structural elements affect the interaction level. The instructor's efforts to generate interaction include the online forum activities as part of grading systems. Student's attitude and behavior changes significantly when the instructor assigns forum activities as a grading component. We theorize that course material that is organized into logical and understandable components will lead to the high levels of interaction between the instructor and students and between students and students. Thus, we hypothesize:

H_1: There will be a positive relationship between perceptions of course structure and student/instructor interaction.

2.1.2 Student Self-Motivation

One of the stark contrasts between successful students is their apparent ability to motivate themselves, even when they do not have the burning desire to complete a certain task. On the other hand, less successful students tend to have difficulty in calling up self-motivation skills, like goal setting, verbal reinforcement, self-rewards, and punishment control techniques (Dembo and Eaton, 2000). The extant literature suggests that students with strong motivation will be more successful and tend to learn the most in web-based courses than those with less motivation (Frankola, 2001); (LaRose and Whitten, 2000). Students' motivation is a major factor that affects the attrition and completion rates in the web-based course and a lack of motivation is also linked to high dropout rates (Frankola, 2001); (Galusha, 1997). It is conceivable that a high level of student motivation be positively related to a high level of interaction with the instructor and students. Thus, we hypothesize:

H_2: There will be a positive relationship between student motivation and student/instructor interaction.

2.1.3 Students' Learning Style

We assume that online learning systems may include less sound or oral components than traditional face-to-face course delivery systems and that online learning systems have more proportion of read/write assignment components, Students with visual learning styles and read/write learning styles may do better in online courses than their counterparts in face-to-face courses. There are some empirical studies that investigated the direct relationships between interaction and students' perceived learning outcomes and satisfactions in university e-learning (Eom et al., 2006). But there are few studies that explore the interaction construct as a mediating variable that connects three other attributes (learning styles, motivation, and course structures).

It is conceivable that there is some association between styles of learning and the level of interaction. For example, Gardner's theory of multiple intelligence categorizes eight different learning styles (Gardner, 1983). Of these, interpersonal learners learn better when they work together, while intrapersonal learners do better in individual and self-paced projects by working alone. Research indicates that learning styles can be incorporated as a key feature for group formation, which in turn may affect the final results of the tasks accomplished by them collaboratively (Alfonseca et al., 2006). This implicitly assumes a positive association between learning styles and the level of interaction. Therefore, we hypothesize:

H_3: There will be a positive relationship between visual and read/write learning styles and student/instructor interaction.

2.1.4 Instructor

Some of widely accepted learning models are objectivism, constructivism, collaborativism, cognitive information processing, and socioculturalism (Leidner and Jarvenpaa, 1995). Distance learning can easily break a major assumption of objectivism – instructor houses all necessary knowledge. For this reason, distance learning systems can utilize many other learning models such as constructivist, collaboratism, and socioculturism. Constructivism assumes that individuals learn better when they control the pace of learning. Therefore, the instructor supports learner-centered active learning. Under the model of collaboratism, student involvement is critical to learning and the instructor becomes discussion leader. Socioculturism models necessitate empowering students with freedom and responsibilities since learning is individualistic.

e-Learning environments demand a transition of the roles of students and the instructor. The instructor's role is to become a facilitator who stimulates, guides and challenges their students via empowering them with freedom and responsibility, rather than a lecturer who focuses on the delivery of instruction. (Huynh, 2005). The importance of the level of encouragement can be found in the model proposed by Lam (2005). We added the two questions to assess the roles of the instructor as the facilitator and stimulator: The instructor was actively involved in facilitating this course; The instructor stimulated students to intellectual effort beyond that required by face-to-face courses. Therefore, we hypothesize:

H_4: There will be a positive relationship between instructor knowledge and facilitation and student/instructor interaction.

H_7: There will be a positive relationship between instructor knowledge and facilitation and learning outcomes.

2.1.5 Instructor Feedback

Instructor feedback to the learner is defined as information a learner receives about his or her learning process and achievement outcomes (Butler and Winne, 1995) and it is "one of the most powerful component in the learning process" (Dick and Carey, 1990, p.165). It intends to improve student performance via informing students how well they are doing and via directing students learning efforts. Instructor feedback in the Web-based system includes the simplest cognitive feedback (e.g., exam/assignment with his or her answer marked wrong), diagnostic feedback (e.g., exam/assignment with instructor comments why the answers are correct or incorrect), prescriptive feedback (instructor feedback suggesting how the correct responses can be constructed) via replies to student e-mails, graded work with comments, online grade books, and synchronous and asynchronous commentary.

Instructor feedback to students can improve learner affective responses, increase cognitive skills and knowledge, and activate metacognition. Metacognition refers to the awareness and control of cognition through planning, monitoring, and regulating cognitive activities (Pintrich et al., 1991). Metacognitive feedback concerning learner progress directs the learner's attention to learning outcomes (Ley, 1999). When metacognition is activated, students may become self-regulated learners. They can set specific learning outcomes and monitor the effectiveness of their learning methods or strategies (Chen, 2002); (Zimmerman, 1989). Therefore, we hypothesize:

H_5: There will be a positive relationship between instructor feedback and student/instructor interaction.

H_8: There will be a positive relationship between instructor feedback and learning outcomes.

2.2 Consequences of Interaction

Interaction between participants in online courses has been recognized as the most important construct of the dimensions determining Web-based course quality. Hence, many studies have shown that interaction is highly correlated to the learning effectiveness of Web-based courses and most students who reported higher levels of interaction with content, instructor, and peers reported higher levels of satisfaction and higher levels of learning. (Moore, 1989); (Swan, 2001); (Vaverek and Saunders, 1993).

Interaction with the Instructor: The learner-instructor interaction involves direct interaction between instructor and learner, and may be initiated by either. Interactions include answering questions about both course content and organization, providing personal examples of class material, demonstrating a sense of humor about the course material, and, importantly, inviting students to seek feedback (Arbaugh, 2001); (Saltzberg and Polyson, 1995). High levels of learner-instructor interaction are positively related with levels of satisfaction with the course and levels of learning (Arbaugh, 2000); (Swan, 2001). Furthermore, Picciano (1998) discovered that students perceive learning from online courses to be related to the amount of discussion actually taking place in them. When students actively participate in an intellectual exchange with fellow students and the instructor, students verbalize what they are learning in a course and articulate their current understanding(Chi and VanLehn, 1991). Therefore, we hypothesize:

H_6: There will be a positive relationship between interaction and learning outcomes.

The last hypothesis tests a positive association between learning outcomes and students' satisfaction. Depending on how each indicator of user satisfaction and learning outcomes are measured, these construct can be reciprocal. In this study, learning outcomes are measured by perceived level of learning, perceived quality of the learning experience in online courses, whereas user satisfaction is measured by the degree of willingness by students to take an online course and to recommend the course taken to other students in the future. Consequently, learning outcomes precede user satisfaction. Therefore we hypothesize:

H_9: There will be a positive relationship between learning outcomes and user satisfaction.

3 SURVEY INSTRUMENT

The survey instrument was designed after conducting an extensive literature review and adapting items from the commonly administered IDEA (Individual Development & Educational Assessment) student rating systems developed by Kansas State University (see Appendix A). In an effort to survey students using technology-enhanced e-learning systems, we focused on students enrolled in Web-based courses with no on campus meetings. A survey URL and instructions were sent to 1,854 student email addresses that were collected from student data files associated with every online course delivered through the online program of a university in the Midwest of the United States. Three hundred and ninety seven valid unduplicated responses were collected from the survey.

4 RESEARCH METHODOLOGY

The hypotheses were tested using a quantitative survey of satisfaction and learning outcome perceptions of students who had taken at least one online course at a large Midwestern university in the United States. Relationships between variables were tested using the structural equation modeling (SEM) tool PLS graph version 3.0, build 1126.

4.1 Measurement Model Estimation

The test of the measurement model included an estimation of the internal consistency and the convergent and discriminant validity of the instrument items.

Table 1: Convergent and discriminant validity of the model constructs.

	loading	t-statistic#
Course Structure (ic=0.88 ave =0.73)		
Struc1	0.8346	14.8330
Struc2	0.8850	18.2017
Struc3	0.8324	11.7576
Instructor Feedback (ic = 0.93 ave = 0.77)		
Feed1	0.8722	24.2528
Feed2	0.8286	18.8518
Feed3	0.9045	30.9556
Feed4	0.9035	26.8712
Self-Motivation (ic = 0.79 ave = 0.66)		
Moti1	0.7156	7.1801
Moti2	0.8989	14.2685
Learning Style (ic = 0.81 ave = 0.67)		
Styl1	0.8681	7.8532
Styl2	0.7707	5.4517
Interaction (ic = 0.76 ave = 0.62)		
Intr1	0.9258	17.1161
Intr2	0.6063	6.9865
Instructor Knowledge & Facilitation (ic = 0.89 ave = 0.73)		
Inst1	0.8396	17.0887
Inst2	0.9026	26.9581
Inst3	0.8125	17.9503
User Satisfaction (ic = 0.90 ave = 0.76)		
Sati1	0.8676	28.3807
Sati2	0.8984	35.8619
Sati3	0.8398	30.6980
Learning Outcomes (ic = 0.91 ave = 0.78		
Outc1	0.8678	22.5078
Outc2	0.8887	33.3322
Outc3	0.8930	35.1271

Note: 'ic' is internal consistency measure; 'ave' is average variance extracted.

All significant $p < .05$.

The composite reliability of a block of indicators measuring a construct was assessed with two measures - the composite reliability measure of internal consistency and average variance extracted (AVE). All reliability measures were above the recommended level of 0.70 (Table 1), thus indicating adequate internal consistency (Fornell and Bookstein, 1982); (Nunnally, 1978). The average variance extracted scores (AVE) were also above the minimum threshold of 0.5 (Chin, 1998b); (Fornell and Larcker, 1981) and ranged from 0.62 to 0.78 (see Table 1). When AVE is greater than 0.50, the variance shared with a construct and its measures is greater than error. This level was achieved for all of the model constructs.

Convergent validity is demonstrated when items load highly (loading >0.50) on their associated factors. Loadings of 0.5 are considered acceptable if there are additional indicators in the block for comparative purposes (Chin, 1998b). Ideally however, they should be 0.7 or higher. Table 1 shows that with the exception of one item, all loadings were above 0.7 for the items measuring each of the eight constructs.

Discriminant validity was firstly assessed by examining the cross-loadings of the constructs and the measures. This analysis revealed that the correlations of each construct with its measures were higher than the correlations with any other measures. Second, the square root of the average variance extracted (AVE) for each construct was compared with the correlation between the construct and other constructs in the model (Chin, 1998b); (Fornell and Larcker, 1981). Table 2 shows that the square root of each AVE is larger than any correlation among any pair of constructs thus indicating discriminant validity.

Table 2: Correlation among construct scores (square root of AVE in the diagonal).

	CS	IF	SM	LS	INT	IKF	US	LO
CS	**.85**							
IF	.72	**.87**						
SM	.26	.23	**.81**					
LS	.29	.21	.25	**.82**				
INT	.44	.59	.38	.26	**.79**			
IKF	.68	.80	.25	.26	.55	**.85**		
US	.74	.69	.36	.41	.53	.71	**.87**	
LO	.56	.49	.35	.44	.45	.55	.78	**.88**

4.2 Structural Model Results

Consistent with the distribution free, predictive approach of PLS (Wold, 1985), the structural model was evaluated using the R^2 for the dependent constructs, the Stone-Geisser Q-square test (Geisser, 1975); (Stone, 1974) for predictive relevance, and the size, t-statistics and significance level of the structural path coefficients. The *t*-statistics were estimated using the bootstrap resampling procedure (100 resamples). The results of the structural model are summarized in Table 3.

Table 3: Structural (inner) model results.

Dependent variables

	Interaction	Learning Outcomes	User Satisfaction
Constructs			
Instructor Knowledge & Facilitation	.151**	.384****	-
Instructor Feedback	.466****	.077 ns	-
Course Structure	-.086 ns	-	-
Self-Motivation	.238****	-	-
Learning Style	.088**	-	-
Student/Instructor Interaction	-	.189***	-
User Satisfaction	-	-	-
Learning Outcomes	-	-	.526****

P-values: **** 0.001, *** 0.01, **0.05, ns - not significant
Effect on Interaction R^2=0.44, Learning Outcomes R^2=0.33, Effect on User Satisfaction R^2=0.61.

The results show that the structural model explains 43.7 percent of the variance in the student/instructor interaction construct, 33.4 percent of the variance in the learning outcomes construct and 61.2 percent of the variance in the user satisfaction construct. The percentage of variance explained for these primary dependent variables is greater than 10 percent implying satisfactory and substantive value and predictive power of the PLS model (Falk and Miller, 1992).

As can be seen from the results, four of the five antecedent constructs hypothesized to directly affect student/instructor interaction are significant. The magnitude of the path coefficients however, indicate that instructor feedback (β = 0.47, t = 5.83) and self-motivation (β = 0.24, t = 4.90) are stronger predictors of interaction relative to instructor knowledge and facilitation (β = 0.15, t = 2.09) and learning style (β = 0.09, t = 1.93). Course structure has no significant relationship with student/instructor interaction (β = -0.09, t = 1.46). H1 is therefore rejected while support exists for H2-H5.

Two of the three antecedent constructs hypothesized to directly affect learning outcomes are significant - instructor knowledge/facilitation (β = 0.38, t = 5.37) and student/instructor interaction (β = 0.19, t = 3.02). H_6 and H_7 are therefore supported. Instructor feedback has no significant impact on learning outcomes (β = 0.08, t = 0.94). H_8 is therefore rejected. Finally, the hypothesized direct relationship between learning outcomes and user satisfaction is significant (β = 0.78, t = 41.74). H_9 is therefore supported.

Although PLS estimation does not utilize formal indices to assess overall goodness-of-fit (GoF) such as GFI, CFI, chi-square values, NNFI and RMSEA, it can be demonstrated by strong factor loadings, high R^2 values and substantial and statistically significant structural paths (Chin, 1998a; 1998b); (Tenenhaus et al., 2005). Tenenhaus et al., (2005) have also developed an additional GoF measure for PLS based on taking the square root of the product of the variance extracted with all constructs with multiple indicators and the average R^2 value of the endogenous constructs. In the currents study the GoF measure is .577 which indicates very good fit (Cohen, 1988).

In addition to examining R^2, the PLS model was also evaluated by looking at the Q-square for predictive relevance for the model constructs. Q-square is a measure of how well the observed values are reproduced by the model and its parameter estimates. Q-squares greater than 0 indicate that the model has predictive relevance, whereas Q-squares less than 0 suggest that the model lacks predictive relevance. In the current study, Q-square values are 0.15 for student/instructor interaction, 0.09 for learning outcomes and 0.42 for user satisfaction.

5 CONCLUSIONS

This study, applying structural equation modeling, examines the effects of interactions and instructor feedback and facilitation on students' satisfaction and their perceived learning outcomes in the context of university online courses. Independent variables included in the study are course structure, self-motivation, learning style, and interaction. A total of 397 valid unduplicated responses from students who have completed at least one online course at a university in the Midwest were used to examine the structural model.

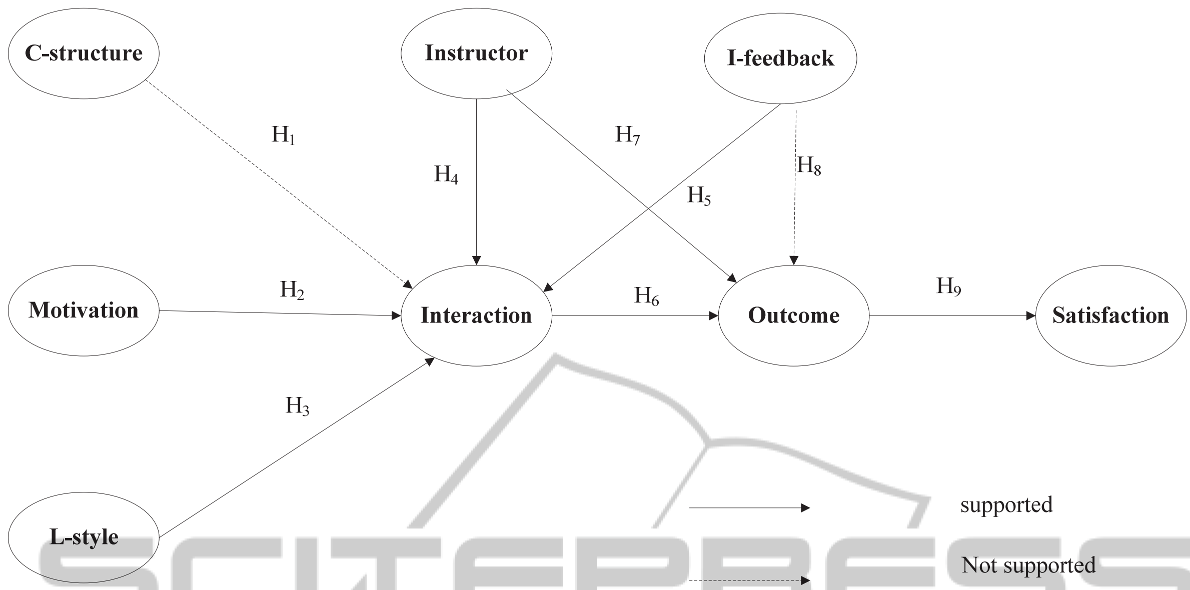

Figure 2: Structural model results.

SCITEPRESS
SCIENCE AND TECHNOLOGY PUBLICATIONS

The results indicate that four of the five antecedent constructs hypothesized to directly affect student/instructor interaction are significant. The magnitude of the path coefficients however, indicate that instructor feedback and self-motivation are stronger predictors of interaction relative to instructor knowledge and facilitation and learning style. Course structure has no significant relationship with student/instructor interaction. Two of the three antecedent constructs hypothesized to directly affect learning outcomes are significant – instructor knowledge/facilitation and student/instructor interaction. Instructor feedback has no significant impact on learning outcomes. Finally, the hypothesized direct relationship between learning outcomes and user satisfaction is significant.

One of the crucial research questions we attempted to answer was the relationship between interaction and perceived learning outcomes. Contrary to previous research (LaPointe and Gunawardena, 2004), the study of Eom et al., (2006) found no support for a positive relationship between interaction and perceived learning outcomes. However, the new research model (figure 1) in the current study presents interaction as the key mediating variable along with instructor feedback and facilitation. Consequently, interactions with the instructor and among students are a strong predictor of student learning outcomes due to the combination of direct effects of interaction on students learning outcomes and indirect effects of course structure, motivation, and learning styles on students learning outcomes.

Our research attempted to include a mediating variable (interaction) to connect course structure and learning outcomes. A possible explanation for the statistically insignificant relationship between online course structure and perceived learning outcomes is that all indicators of course structure may have not included expected class participation in the form of online conferencing systems.

Our results indicated that instructor feedback and self-motivation are stronger predictors of interaction relative to instructor knowledge and facilitation and learning style. Therefore, self-motivation is indirectly affecting students learning outcomes via the interaction construct.

This research, along with the study of Eom, et al. (Eom et al., 2006) has made a critical contribution in e-learning empirical research by identifying two critical human factors that make e-learning a superior mode of instruction. In our view, this is a significant shift of direction in e-learning empirical research. Our research provides strong empirical evidence that online education is not a universal innovation applicable to all types of instructional situations. Online education can be a superior mode of instruction if it is targeted to learners with specific learning styles (visual and read/write learning styles) (Eom et al., 2006) and students personality characteristics (Schniederjans and Kim, 2005) and with timely, helpful instructor feedback of various types. Proper management of human factors can change the dynamics of e-learning process to produce e-learning outcomes surpass those provided in classroom-based settings. Technology in e-learning is just an instructional tool. We conclude that instructor's facilitating roles and feedback is the most critical factor in e-learning that changes the e-learning process positively and that changes learner-instructor relationship positively to make e-learning a superior mode of instruction.

REFERENCES

Akyol, Z. and Garrison, D. R. (2011) In *Student Satisfaction and Learning Outcomes in e-Learning: An introduction to empirical research* (Eds, Eom, S. B. and Arbaugh, J. B.) Information Science Reference (an imprint of IGI Global), Hersey, PA, pp. 23-35.

Alexander, M. W., Perrault, H., Zhao, J. J. and Waldman, L. (2009) In *Journal of Educators Online*, Vol. 6.

Alfonseca, E., Carro, R. M., Martín, E., Ortigosa, A. and Paredes, P. (2006) *User Modeling and User - Adapted Interaction,* 16, 377-401.

Arbaugh, J. B. (2000) *Business Communication Quarterly,* 63, 9-18.

Arbaugh, J. B. (2001) *Business Communication Quarterly,* 64, 42-54.

Arbaugh, J. B., Godfrey, M. R., Johnson, M., Pollack, B. L., Niendorf, B. and Wresch, W. (2009) *Internet and Higher Education,* 12, 71-87.

Bonk, C. J. (2009) *The World is Open: How Web Technology is Revolutionizing Education* Jossey-Bass, San Francisco, CA

Butler, D. L. and Winne, P. H. (1995) *Review of Educational Research,* 65, 245-281.

Chen, C. S. (2002) *Information Technology, Learning, and Performance Journal,* 20, 11-25.

Chi, M. T. and VanLehn, K. A. (1991) *The Journal of Learning Sciences,* 1, 69-105.

Chin, W. W. (1998a) *MIS Quarterly,* 22, VII-XVI.

Chin, W. W. (1998b) In *Modern Methods for Business Research*(Ed, Marcoulides, G. A.) Lawrence Erlbaum Associates, Mahwah, NJ, pp. 295-336.

Cohen, J. (1988) *Statistical Power Analysis for the Behavioral Sciences* Lawrence Erlbaum Associates, publishers, Hillsdale, NJ.

Dembo, M. and Eaton, M. (2000) *The Elementary School Journal,* 100, 473-490.

Dick, W. and Carey, L. (1990) *The Systematic Design of Instruction,* Harper Collins Publishers, New York, NY.

Dunn, R., Beaudry, J. and Klavas, A. (1989) *Education Leadership,* 46, 50-58.

Eom, S. B., Ashill, N. and Wen, H. J. (2006) *Decision Sciences Journal of Innovative Education,* 4, 215-236.

Falk, R. F. and Miller, N. B. (1992) *A primer for soft modeling,* The University of Akron Press, Akron, OH.

Fornell, C. R. and Bookstein, F. L. (1982) In *A second Generation of multivariate analysis*(Ed, Fornell, C.) Praeger, New York, pp. 289-394

Fornell, C. R. and Larcker, D. (1981) *Journal of Marketing Research,* 18, 39-50.

Frankola, K. (2001) *Workforce,* 80, 53-60.

Galusha, J. M. (1997) *Interpersonal Computing and Technology: An Electronic Journal for the 21st Century,* 5, 6-14.

Gardner, H. (1983) *Frames of Mind: The Theory of Multiple Intelligences,* Basic Books, New York.

Garrison, D. R. (2009) In *Encyclopedia of distance and online learning learning*(Ed, Howard, C.) IGI Global, Hersey, PA, pp. 352-355.

Garrison, D. R. and Anderson, T. (2003) *E-learning in the 21st century: A framework for research and practice,* Routledge/Falmer, London, UK.

Geisser, S. (1975) *Journal of the American Statistical Association,* 70, 320-328.

Hayes, S. K. (2007) *MERLOT Journal of Online Teaching and Learning,* 3, 460-465.

Haytko, D. L. (2001) *Marketing Education Review,* 11, 27-39.

Huynh, M. Q. (2005) *Journal of Electronic Commerce in Organizations,* 3, 33-45.

Kellogg, D. L. and Smith, M. A. (2009) *Decision Sciences Journal of Innovative Education,* 7, 433-454.

Lam, W. (2005) *Journal of Electronic Commerce in Organizations,* 3, 18-41.

LaPointe, D. K. and Gunawardena, C. N. (2004) *Distance Education,* 25, 83-106.

LaRose, R. and Whitten, P. (2000) *Communication Education,* 49, 320-338.

Leidner, D. E. and Jarvenpaa, S. L. (1995) *MIS Quarterly,* 19, 265-291.

Ley, K. (1999) *Campus-Wide Information Systems,* 16, 63-70.

Liu, X., Magjuka, R. J., Bonk, C. J. and Lee, S. (2007) *Quarterly Review of Distance Education,* 8, 9-24.

Marriott, N., Marriott, P. and Selwyn, N. (2004) *Accounting Education,* 13, 117-130.

Means, B., Toyama, Y., Murphy, R., Bakia, M. and Jones, K. (2009) U.S. Department of Education, Washington, DC.

Moore, M. G. (1989) *The American Journal of Distance Education,* 3, 1-6.

Moore, M. G. (1991) *The American Journal of Distance Education,* 5, 1-6.

Morgan, G. and Adams, J. (2009) *Journal of Interactive Learning Research,* 20, 129-155.

Northrup, P. T. (2002) *The Quarterly Review of Distance Education,* 3, 219-226.

Nunnally, J. C. (1978) *Psychometric Theory,* McGraw-Hill, New York.

Peltier, J. W., Drago, W. and Schibrowsky, J. A. (2003) *Journal of Marketing Education,* 25, 260-276.

Picciano, A. (1998) *Journal of Asynchronous Learning Networks,* 12, 1-14.

Piccoli, G., Ahmad, R. and Ives, B. (2001) *MIS Quarterly,* 25, 401-426.

Pintrich, P. R., Smith, D. A., Garcia, T. and McKeachie, W. J. (1991) *A manual for the use of the Motivated Strategies for Learning Questionnaire (MSLQ),* National Center for Research to Improve Postsecondary Teaching and Learning, Ann Arbor:

University of Michigan.
Saltzberg, S. and Polyson, S. (1995) *Syllabus,* 9, 26-28.
Sarker, S. and Nicholson, J. (2005) *Informing Science,* 8, 55-73.
Schniederjans, M. J. and Kim, E. B. (2005) *Decision Sciences: Journal of Innovative Education,* 3, 205-221.
Sitzmann, T., Kraiger, K., Stewart, D. and Wisher, R. (2006) *Personnel Psychology,* 59, 623-664.
Stone, M. (1974) *Journal of The Royal Statistical Society,* 36, 111-147.
Swan, K. (2001) *Distance Education,* 22, 306-331.
Tanner, J. R., Noser, T. C. and Totaro, M. W. (2009) *Journal of Information Systems Education,* 20, 29-40.
Tenenhaus, M., Vinzi, V. E., Yves-Marie, C. and Lauro, C. (2005) *Computational Statistics and Data Analysis,* 48, 159-205.
Vaverek, K. A. and Saunders, C. (1993) *Journal of Educational Technology Systems,* 22, 23-39.
Wilkes, R. B., Simon, J. C. and Brooks, L. D. (2006) *Journal of Information Systems Education,* 17, 131-140.
Wold, H. (1985) In *Measuring The Unmeasurable* (Eds, Nijkamp, P., Leitner, H. and Wrigley, N.) Martinus Nijhoff, Dordrecht, pp. 221-252.
Zimmerman, B. J. (1989) In *Self regulated learning and academic achievement: Theory, research, and practice* (Eds, Zimmerman, B. J. and Schunk, D. H.) Springer-Verlag, New York, pp. 1-25.

APPENDIX

Instructor
Inst1 = The instructor was very knowledgeable about the course
Inst2 = The instructor was actively involved in facilitating this course
Inst3 = The instructor stimulated students to intellectual effort beyond that required by face-to-face courses.

Course Structure
Struc1 =The overall usability of the course Web site was good.
Struc2 =The course objectives and procedures were clearly communicated.
Struc3 =The course material was organized into logical and understandable components.

Feedback
Feed1 = The instructor was responsive to student concerns.
Feed2 = The instructor provided timely feedback on assignments, exams, or projects.
Feed3 = The instructor provided helpful timely feedback on assignments, exams, or projects.
Feed 4 = I felt as if the instructor cared about my individual learning in this course.

Self-Motivation
Moti1 = I am goal directed, if I set my sights on a result, I usually can achieve it.
Moti2 = I put forth the same effort in on-line courses as I would in a face-to-face course.

Learning Style
Styl1 = I prefer to express my ideas and thoughts in writing, as opposed to oral expression.
Styl2 = I understand directions better when I see a map than when I receive oral directions.

Interaction
Intr1 = I frequently interacted with the instructor in this on-line course.
Intr2 = I frequently interacted with other students in this on-line course.

OUTPUTS
User Satisfaction
Sati1 = The academic quality was on par with face-to-face courses I've taken.
Sati2 = I would recommend this course to other students.
Sati3 = I would take an on-line course at Southeast again in the future.

Learning Outcomes
Outc1 = I feel that I learned as much from this course as I might have from a face-to-face version of the course.

Outc2 = I feel that I learn more in on-line courses than in face-to-face courses.

Outc3 = The quality of the learning experience in on-line courses is better than in face-to-face courses.