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The Effects of Student Motivation and Self-Regulated Learning Strategies on Student's Perceived E-learning Outcomes and Satisfaction

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THE EFFECTS OF STUDENT MOTIVATION AND SELF-REGULATED LEARNING STRATEGIES ON STUDENTS' PERCEIVED E-LEARNING OUTCOMES AND SATISFACTION

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Abstract:

Several attributes of students, as the primary participants of e-learning systems, have been major subjects of intense research over the past decade. Prior research findings identified a set of 31 determinants that have a significant effect on satisfaction and learning outcomes [Bitzer and Janson, 2014]. Structural equation modeling is applied to examine the effects of intrinsic motivation, extrinsic motivation, and self-regulated learning strategies on e-learners' satisfaction and their perceived learning outcomes in the context of university online courses. A total of 372 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. The results indicated that intrinsic motivation, self-regulated learning strategies affect e-learners' learning outcomes. However, extrinsic student motivation had no significant relationship with learning outcomes. Nevertheless, it affected the self-regulated learning. The findings suggest that intrinsic motivation was the strongest predictors of e-learners' learning outcomes.

Keywords: distance education/ distance learning, intrinsic motivation, extrinsic motivation, self-regulated learning strategies, perceived learning outcomes, and perceived student satisfaction.

The measures for 'Learning Outcomes' seem to be measuring satisfaction with the format rather an actual measure for learning outcomes. Related to this, H1 & H2 are written in a way that is not best measured through SEM. It's not clear where the measures are derived.

I. INTRODUCTION

One of well-known learning effectiveness model is the virtual learning environment (VLE) effectiveness model [Piccoli et al., 2001], which postulated that two antecedents (human dimension and design dimension) determine effectiveness of e-learning systems. The human dimension is concerned with two human entities (students and instructor) and their various attributes, and the design dimension includes learning management systems (LMS), self-regulated learning and learner control, course design, and interaction among e-learning entities.

The essence of e-learning are psychological and cognitive learning processes taking place in students' mind. The students' learning/cognitive process is affected by multiple dimensions of learners' characteristics including biological characteristics/senses (physiological dimension); personality characteristics such as attention, emotion, motivation, and curiosity (affective dimension); information processing styles such as logical analysis, or "gut" feelings (cognitive dimension); and psychological/individual differences (psychological dimension) [Dunn et al., 1989].

The primary objective of this study is to empirically investigate the effects of motivation and self-regulated learning strategies on students' perceived learning outcomes and satisfaction in university online education. The next section reviews the literature on the effects of motivation and self-regulated learning strategies on e-learners' learning outcomes and satisfaction. We follow this with a description of the cross-sectional survey that was used to collect data and the results from a Partial Least Squares (PLS) analysis of the research model. The final section summarizes important findings and discusses the implications of the results for the e-learning area.

II. RESEARCH MODEL AND HYPOTHESES DEVELOPMENT

Motivation is incentive that causes a person to act do a certain thing. According to Ryan and Deci [2000, p.. 56], intrinsic motivation is the psychological feature that makes an individual do an activity for its inherent satisfactions, for fun, or the challenge entailed, rather than for some separable consequence. Extrinsic motivation, on the other hand, makes an individual take an action toward a goal to attain some separable outcome such as rewards, recognition, etc.

Several attributes of students, as the primary participants of e-learning systems, have been major subjects of intense research over the past decade. Prior research findings identified a set of 31 determinants that have a significant effect on satisfaction and learning outcomes [Bitzer and Janson, 2014]. Their findings include several attributes of learners such as prior experience with learning management systems (LMS), computer experience, self-efficacy, learning styles, motivation, metacognition, and learning engagement. Of these, we focus on motivation and self-regulated learning strategies including metacognition, and learning engagement. Self-regulated learning is a pivotal learning strategy to achieve the intended e-learning outcome. Student motivation is a psychological construct that activates the self-regulation process [Zimmerman, 2008].

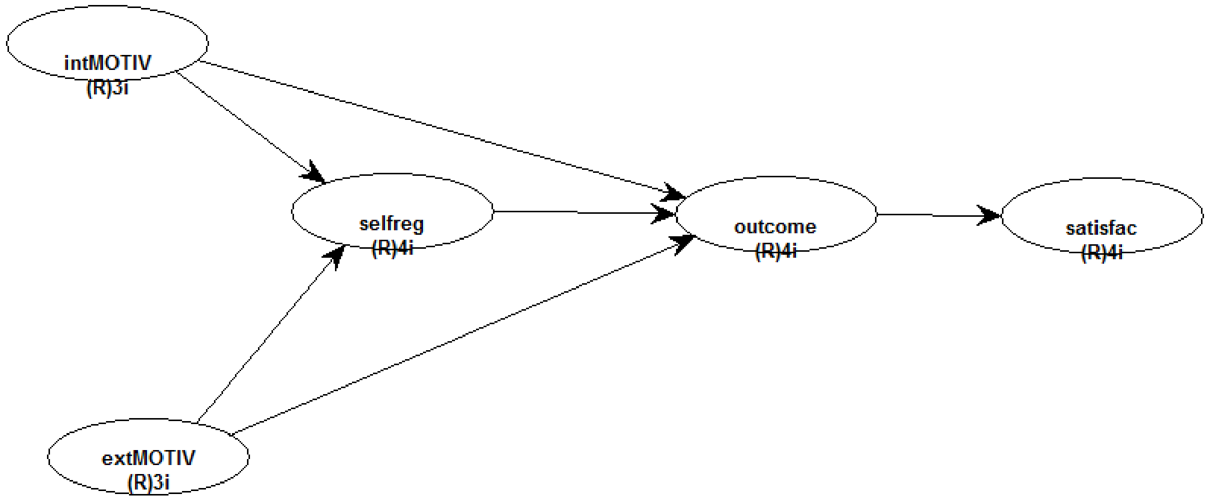

Fig. 1: Research Model

Motivation and Learning Outcomes

Continuing research on motivation has produced some empirical evidence indicating positive links between intrinsic motivation and satisfaction [Eom et al., 2006], between motivation and student performance [Castillo-Merino and Serradell-López, 2014], social media engagement and motivational factors [Alt, 2015], and individual players' peer intrinsic and extrinsic motivation and intention to learn collaboratively and individually in a game-based learning environment [Kong et al., 2012]. Several recent empirical studies which concluded that motivation is the most important construct for explaining online students' ability to pass exams [Chua and Don, 2013; Huet et al., 2011] and that motivation has a direct, positive and significant effect on students' achievement [Castillo-Merino and Serradell-López, 2014]. Therefore, we hypothesized:

> H_1: Students with a higher level of intrinsic motivation in online courses will report higher levels of agreement that the perceived learning outcomes are equal to or better than in face-to-face courses.

> H_2: Students with a higher level of extrinsic motivation in online courses will report higher levels of agreement that the perceived learning outcomes are equal to or better than in face-to-face courses.

Motivation and Self-regulated Learning Strategies

Learning is a process of acquiring knowledge and skills. The learning process consists of planning, organizing, motivating, monitoring, evaluating, and controlling learning efforts and activities. According to Zimmerman [1989, p.329], self-regulated learners are "metacognitively, motivationally, and behaviorally active participants in their own learning process. Such students personally initiate and direct their own efforts to acquire knowledge and skill rather than relying on teachers, parents, or other agents of instruction."

Students' self-regulated learning has three essential features: Self-regulated students (1) select and use their self-regulated learning strategies to achieve desired learning outcomes, (2) continuously monitor the learning process and are responsive to self-oriented feedback about learning effectiveness, and (3) activate their interdependent motivational processes [Zimmermann, 1990]. A repertoire of learning strategies includes rehearsal, elaboration, organization, critical thinking, time/study environmental management, effort regulation, peer learning, help-seeking, and metacognitive self-regulation [Pintrich et al., 1993].

In the e-learning area, students' metacognitive self-regulation and self-esteem in online courses were positively correlated with students' cognitive and emotional engagement [Pellas, 2014]. Cognitive engagement refers to students' active participation and intellectual efforts to create/construct new knowledge in the learning process using cognitive and metacognitive strategies. The metacognitive strategies refer to a wide range of strategies used by learners to become aware of and in control of mental thought, including understanding their cognitive processes, learning their own learning styles, becoming aware of their own cognitive bias, and figuring out the most effective problem-solving strategies. Emotional engagement is concerned with high levels of students' interest and positive attitudes or values associated with the learning process.

Survey and interview findings [Kong et al., 2012] showed that an individual player's peer intrinsic and extrinsic motivations had significantly positive influence on his or her intention to learn collaboratively and individually when playing Massively Multiplayer Online Game. the relationship between theoretically grounded constructs of motivation and various metacognitive processes is examined [Moos, 2014] and it was found that extrinsic motivation significantly predicted the extent to which participants monitored their learning task goals with hypermedia. Therefore, we hypothesized:

H3: Intrinsic motivation will be positively related to the level of self-regulated learning.

H_4: Extrinsic motivation will be positively related to the level of self-regulated learning.

Self-Regulated Learning Strategies and Learning Outcome

Several empirical studies support Zimmerman's theory. A systematic review of past research from 2004 to 2014 examining self-regulated learning strategies and academic achievement in online higher education learning environments revealed that the strategies of time management, metacognition, effort regulation, and critical thinking were positively correlated with academic outcomes, but on the other hand rehearsal, elaboration, and organization had the least empirical support [Broadbent and Poon, 2015]. Moreover, students' use of the SRL strategies (metacognition, time management, and effort regulation) in a traditional face-to-face learning environment was strongly associated with a higher level of learning outcomes and it was a significant predictor of students' learning outcomes [Richardson et al., 2012]. Therefore, we hypothesized:

H_5: A higher level of student self-regulation will lead to higher levels of student agreement that the learning outcomes of online courses are equal to or better than in face-to-face courses.

Outcome and Satisfaction

E-learners' learning outcomes and satisfaction have been two major dependent constructs in e-learning empirical studies [Eom et al., 2006; Marks et al., 2005]. In this study, learning outcomes are measured by the perceived level of students' quality of learning experience in online classes. Students' satisfaction is measured by their willingness to take online classes again or to recommend the instructor of online classes taken to other students. Thus, we hypothesized:

H_6: learning outcome will be positively related to e-learners' satisfaction.

III. SURVEY INSTRUMENT AND SAMPLE

The survey questionnaire (see Appendix A) is selected from a previous study [Eom et al., 2006] which is in part adapted from the commonly administered IDEA (Individual Development & Educational Assessment) student rating system developed by Kansas State University. In addition, the questionnaire on motivation and student self-regulation was adapted in part from the Motivated Strategies for Learning Questionnaire (MSLQ) [Pintrich et al., 1993], an 81-item, self-report instrument designed to measure college students' motivational orientations and their use of different learning strategies [Pintrich et al., 1991]. We collected the e-mail addresses of 3285 students from the student data files achieved with every online course delivered through the online program of a university in the Midwestern United States. The 41 survey questions were created using SurveyMonkey©. The survey URL and instructions were sent to 3285 e-mail addresses. We collected 382 valid unduplicated responses from the survey (11.63% response rate). Of these responses, 10 incomplete responses with missing values were deleted.

IV. METHODOLOGY

The research model (figure 1) is tested using WarpPLS, which is the structural equation modeling (SEM)-based Partial Least Squares (PLS) methodology. Model fit and quality indices were all acceptable levels.

Measurement (Outer) Model Estimation

The first step in data analysis involves model estimation. The test of the measurement model includes an estimation of the internal consistency and the convergent, discriminant, and factorial validity of the instrument items, as suggested by Straub et al. [2004]. All reliability measures were above the recommended level of 0.70., thus indicating adequate internal consistency [Bernstein, 1994; Fornell and Bookstein, 1982]. The average variance extracted scores (AVE) were also above the minimum threshold of 0.5 [Chin, 1998; Fornell and Larcker, 1981] and ranged from 0.57 to 0.76. When AVE is greater than .50, the variance shared with a construct and its measures is greater than error. This level was achieved for all of the model constructs.

Construct Validity

Construct validity is assessed through establishing both convergent and discriminant validities. Convergent validity refers to the extent to which a set of indicator variables load together and they load highly (loading >0.50) on their associated factors. Individual reflective measures are considered to be reliable if they correlate more than 0.7 with the construct they intend to measure. Table 1 shows most of the loadings, except q34, were higher than the threshold value .7. When indicator variables do not cross-load on two or more constructs, each construct is said to be demonstrating discriminant validity. In PLS, discriminant validity was assessed using two methods. First, by examining the cross-loadings of the constructs and the measures; Second, by comparing the square root of the average variance extracted (AVE) for each construct with the correlation between the construct and other constructs in the model [Chin, 1998; Fornell and Larcker, 1981]. All constructs in the estimated model fulfilled the condition of discriminant validity (see Table 1).

Table 1: Model Validation Results

	intMOTI	extMOTI	selfreg	outcome	satisfa
q6	0.984	-0.036	0.11	0.114	-0.073
q7	0.986	0.033	-0.101	-0.105	0.067
q9	0.058	0.852	0.516	-0.061	-0.032
q10	-0.018	0.97	-0.208	0.116	-0.048
q11	-0.018	0.988	-0.104	-0.086	0.071
q30	0.035	-0.062	0.989	0.126	-0.039
q31	-0.049	0.089	0.994	0.023	-0.04
q32	-0.115	0.084	0.984	-0.094	0.042
q33	0.159	-0.14	0.977	-0.023	0.027
q34	-0.013	-0.058	0.065	0.673	0.734
q35	-0.026	0.027	0.064	0.782	0.619
q36	0.01	-0.003	-0.022	0.936	-0.351
q37	0.009	0.019	-0.041	0.947	-0.317
q38	0.022	0.013	-0.129	-0.204	0.97
q39	-0.028	-0.029	0.052	-0.137	0.988
q40	0.026	-0.001	0.208	0.519	0.828
q41	-0.005	0.021	-0.009	0.162	0.986
Compo. RC	0.844	0.795	0.841	0.93	0.923
Cronbach's AC	0.63	0.613	0.747	0.899	0.886
AVE	0.73	0.747	0.57	0.767	0.752

Notes: Loadings and cross-loadings shown are after oblique rotation and Kaiser normalization. Composite RC: Composite Reliability Coefficients; Cronbach's AC: Cronbach's Alpha Coefficients; AVE: average variance extracted, # All significant $p < .05$.

Reliability

Reliability is concerned with the measurement accuracy within a construct while construct validity applies to the measurement between constructs. 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). The internal consistency, Cronbach's alpha, is a measure of the extent to which a set of indicators of a latent construct are highly interrelated and therefore measure the same latent construct [Hair et al., 2010]. All reliability measures were above the recommended level of 0.70 (Table 1), thus indicating adequate internal consistency [Bernstein, 1994; Fornell and Bookstein, 1982]. The average variance extracted scores (AVE) were also above the minimum threshold of 0.5 [Chin, 1998; Fornell and Larcker, 1981] and ranged from 0.72 to 0.913 (see Table 1). When AVE is greater than .50, the variance shared with a construct and its measures is greater than error. This level was achieved for all of the model constructs. Overall, the measurement model results provided support for the factorial, convergent, and discriminant validities and reliability of the measures used in the study.

Structural (Inner) Model Results

Since PLS makes no distributional assumptions in its parameter estimation procedure, traditional parameter-based techniques for significance testing and model evaluation are considered to be inappropriate. Consistent with the distribution-free, predictive approach of PLS [Wold, 1985], the structural model was evaluated using the *R*-square for the dependent constructs, and the size, *t*-statistics, and significance level of the structural path coefficients. Table 4 shows the results of the warpPLS analysis, including the path coefficients, as well as the bootstrapped t-values (based on 1000 bootstrapping runs). The results show that the structural model explains 71% of the variance in user satisfaction, and 64% of the variance in learning outcomes. The percentage of variance explained for these two primary dependent variables is greater than 10 percent, implying satisfactory and substantive value and predictive power of the PLS model [Falk and Miller, 1992].

R-Square for Dependent Constructs

The results show that the structural model explains 15 percent of the variance in the learning outcome construct, and 64 percent of the variance in the user satisfaction construct. The percentage of variance explained for these primary dependent variables were greater than 10 percent implying satisfactory and substantive value and predictive power of the PLS model [Falk and Miller, 1992].

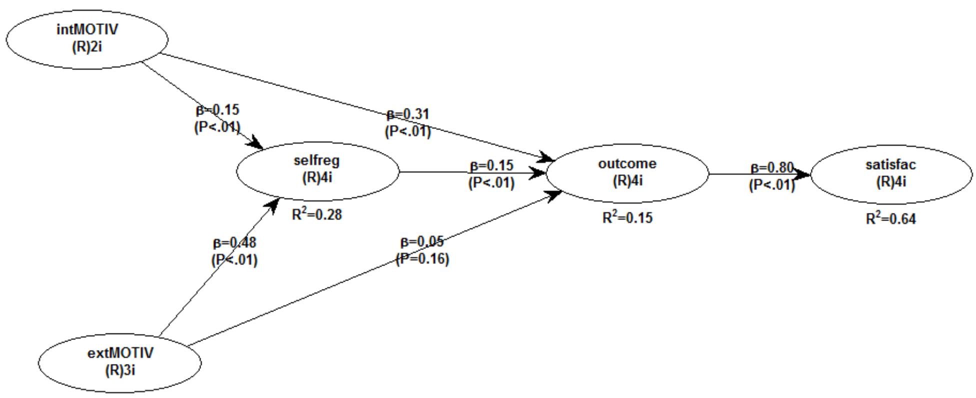

Fig. 2: Structural Model Results

Table 3: Structural (inner) model results

	Path Coefficient	*p* - value	Hypothesis Support
Effects on Learning Outcomes	**R^2 = 0.15**		
Intrinsic Student Motivation (H_1)	+0.31	< .01	Yes
Extrinsic Student Motivation (H_2)	+0.05	= 0.16 n.s	No
Student Self-Regulation (H_5)	+0.15	< .01	Yes
Effects on Self-Regulation	**R^2 = 0.28**		
Intrinsic Student Motivation (H_3)	+0.15	< .01	Yes
Extrinsic Student Motivation (H_4)	+0.48	< .01	Yes
Effects on Satisfaction	**R^2 = 0.64**		
Learning Outcome (H_6)	+0.8	< .01	Yes

n.s. not *significant*

Structural Path Coefficients

As can be seen from the results, of the three antecedent constructs hypothesized to affect learning outcomes, all of them are significant except extrinsic motivation, suggesting that intrinsic motivation directly affects learning outcomes and it activates learner's psychological learning process (self-regulated learning management). Intrinsic student motivation did have a significant positive association with learning outcomes. The results in Table 3 show a significant positive relationship between:

- Intrinsic motivation and self-regulated learning
- Self-regulated learning and learning outcome
- Extrinsic motivation and self-regulated learning
- Learning outcome and e-learner satisfaction

Only Hypothesis H4 was rejected. Extrinsic student motivation had no significant relationship with learning outcomes. The findings indicate that intrinsic student motivation (β = .31) was the strongest predictor of learning outcome followed by self-regulation (β = .15). Extrinsic student motivation had no significant and direct relationship with learning outcomes. Nevertheless, it was the strongest predictor of self-regulation.

V. CONCLUSION AND DISCUSSION

The main contributions of this study are twofold. First, in an earlier study, Eom, Ashill and Wen (2006) found no significant relationships between students' self-motivation and perceived learning outcomes. The motivation construct in the current study is further subdivided into intrinsic and extrinsic motivation. The findings indicate that intrinsic student motivation did have a significant positive association with learning outcomes. Extrinsic student motivation had no significant relationship with learning outcomes. The results of the current study on the effect of intrinsic motivation on learning outcomes are in accordance with the view of educational psychologists such as Zimmerman [Chua and Don, 2013; Huet et al., 2011; 2003] and that motivation has a direct, positive and significant effect on students' achievement [Castillo-Merino and Serradell-López, 2014]. This study has significant implications for distance educators. Instructors teaching online classes should incorporate the inclusion of class assignment material that intellectually challenges e-learners so that they can new things.

Second, as the review of literature shows, there are few empirical studies that directly investigate the relationships among four constructs (intrinsic motivation, extrinsic motivation, self-regulation, and learning outcomes) in university online education. This study provided important empirical evidence in regard to the relationship between intrinsic motivation and self-regulatory learning strategies. The results of this study showed that both intrinsic motivation and extrinsic motivation activate the self-regulation process which in turn positively affect the learning outcomes.

VI. LIMITATIONS AND DIRECTIONS FOR FUTURE RESEARCH

There exists a dynamic relationship among student motivation, instructor's facilitating roles, and students' academic engagement. Cho and Cho [2014] examined the relationship between instructor scaffolding for interaction and students' academic engagement in e-learning and concluded that online instructors' scaffolding for interaction had a significantly positive influence on students' behavioral engagement. The comprehensive picture of the roles of motivation and self-regulation can be identified with the inclusion of other constructs such as instructor, interaction, etc. Therefore, future research needs to further explore the identification of the antecedent of motivation, and the roles of motivation as a mediating variable affecting e-learning outcomes and satisfaction.

The current study's self-regulation construct included the strategies of metacognition, effort regulation, and organization. Future studies should focus on identifying the relationships between each of the self-regulatory learning strategies separately. As discussed in a prior section, prior studies show that students' use of each of the different SRL strategies has different effects on learning outcomes [Broadbent and Poon, 2015; Richardson et al., 2012].

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APPENDIX: SURVEY QUESTIONS

Student Intrinsic Motivation

6. In an online class like this, I prefer class material that really challenges me so I can learn new things.
7. When I have the opportunity in this online class to choose class assignments, I choose the assignments that I can learn from even if they don't guarantee a good grade.
8. I do all that I can do to make my assignments turn out perfectly.

Student Extrinsic Motivation

9. I work hard to get a good grade even when I don't like a class.
10. I want to do well in this online class because it is important to show my ability to my family, parents, or others.
11. I like to be one of the most recognized students in a class

Self-regulation

30. In the beginning, I set my goals and plan accordingly according to what I need to do to make desired learning outcomes.
31. Even when study materials are dull and uninteresting, I keep working until I finish.
32. I keep up with my grades in each course, and if one seems to be sliding I'll stress that class more in my studying.
33. When I study for a test, I try to put together the information from class notes and from the book.

Learning Outcomes

34. The academic quality of this online class is on par with face-to-face classes I've taken.
35. I have learned as much from this online class as I might have from a face-to-ace version of the course.
36. I learn more in online classes than in face-to-face classes.
37. The quality of the learning experience in online classes is better than in face-to -face classes.

User Satisfaction

38. I would recommend this instructor to other students.
39. I would recommend this online class to other students.
40. I would take an online class at this university again in the future.
41. I was very satisfied with this online class.

ABOUT THE AUTHORS

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