Effects of Self-Efficacy and Self-regulated Learning on LMS User Satisfaction and LMS Effectiveness

Full Papers

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Abstract

Over the past decade, numerous studies examined the critical factors that affect the learning outcomes and student satisfaction in asynchronous online learning courses including learning management systems (LMS). This research focuses on the effects of learner’s psychological variables (e.g., self-efficacy) and psychological learning process (e.g., self-regulated learning management) on student satisfaction with the e-learning management system and e-learning systems’ effectiveness. The survey questionnaire is selected from a multi-dimensional model for assessing e-learning systems success (ELSS) from the perspective of the e-learner. The 674 sample consists of 140 business students and 534 non-business students. The research model is tested using WarpPLS, which is the structural equation modeling (SEM)-based Partial Least Squares (PLS) methodology. Statistically significant evidence was found to suggest students’ psychological variables (e.g., self-efficacy) and psychological learning process (e.g., self-regulated learning management) had effects on student e-learning satisfaction. Finally, this study made a new contribution to e-learning literature by providing new empirical evidence that e-learners’ self-self-efficacy has a strong positive relationship with a higher level of e-learners’ self-regulated learning management.

Keywords

Self-efficacy, self-regulated learning, learning management systems, user satisfaction with learning management systems.

Introduction

Over the past decade, numerous studies examined the critical factors that affect the learning outcomes and student satisfaction in asynchronous online learning courses (Eom et al. 2006; Marks et al. 2005; Mashaw 2012; Peltier et al. 2003; Peltier et al. 2007). Their research identified three dimensions of e-learning systems success: human (students, instructors, and interaction among them), design (course contents, course structures, etc.), and e-learning systems including technologies. The technological dimension of e-learning success factors includes the learning management system (LMS) and many information system tools such as intelligent agents, Web 2.0/3.0 technologies, push technologies, blogs, and wikis, to name a few. Needless to say, LMS is an essential determinant of e-learning success and students’ satisfaction.

The term “learning management systems” has been used as either application software or a system of application software, operating systems, and human elements (instructor and students), and course contents and structures working together. In this paper, we view e-learning as an open system that comprised of human subsystems (students and the instructor), LMS subsystem. These three entities continuously interact with each other and with their environments. A LMS is often used with a virtual learning environment (VLE) interchangeably. A VLE refers to an operating system and specialized learning management software that allows students and the instructor to plan, organize, monitor, coordinate, and control the learning activities to facilitate the learning process and to optimize the desired learning outcomes.
The DeLone and McLean (DM) model is one of the widely recognized information system (IS) success models based on a systematic review of 180 studies with over 100 measures. The DM model theorized that system quality and information quality singularly and jointly affect both use and user satisfaction, which in turn, are direct antecedents of system effectiveness (DeLone et al. 1992). The DM model has been empirically tested using structural equation modeling in a quasi-voluntary IS use context (Rai et al. 2002) and in a mandatory information system context (Livari 2005). The study of Rai, et al. concluded that the DM model has explanatory power and therefore the model has merit for explaining IS success. The study of Livari concluded that perceived system quality and information quality are significant predictors of user satisfaction. But his study failed to support the positive association between system use and user satisfaction. To extend the DM model into the e-learning area, a number of studies (Eom et al. 2012; Eom et al. 2011) empirically tested the DeLone and McLean model of information systems success model in a university e-learning context using structural equation modeling. Eom and others (Eom et al. 2012) presented empirical test of the DeLone and McLean model of IS success in a university e-learning context, which is strictly involuntary use. Their study reached several useful conclusions. Perceived system quality and perceived information quality are very strong (high path coefficient) predictor of user satisfaction. Perceived user satisfaction is a very strong predictor of individual impact. Perceived system quality is an insignificant predictor of system use or relatively weak predictor of system use. The direct influence of system use on user satisfaction is weak even though it is statistically significant. In order for e-learning students to be successful, they must be provided with e-learning system that provides information they need and user-friendly. Although system quality has not directly contributed to predict individual impact, its impact is indirect. System quality and information quality have positive effects on user satisfaction. Information quality has also positive effects on system use, which in turn positively contributes to user satisfaction. Therefore, all the antecedent variables are positively affecting e-learning outcomes either indirectly or directly. System quality and information quality are necessary conditions for e-learning success and students' satisfaction with LMS, but not sufficient conditions.

The conceptual framework of Piccoli, Ahmad and Ives (2001) postulates that human and design factors as antecedents of learning effectiveness. Human factors are concerned with students and instructors, while design factors characterize such variables as learning model, technology, learner control, course content, and interaction. According to Piccoli et al (2001), the technology construct can be measured by quality and reliability, accessibility of LMS. The VLE model is a broad framework of VLE effectiveness which postulated that human and design dimensions determine e-learning effectiveness. The design dimension consists of five constructs including technology and learner control.

The purpose of this paper is to empirically investigate the effects of self-efficacy and self-regulated learning on learner satisfaction with LMS and LMS effectiveness. Our research model is an extension of the information systems success model of DeLone and McLean (1992) and the virtual learning environment (VLE) effectiveness model of Piccoli et al.(2001). This research focuses on the effects of learner’s psychological variables (e.g., self-efficacy) and psychological learning process (e.g., self-regulated learning management) on student satisfaction with the e-learning management system and e-learning systems’ effectiveness. This research idea is derived on a technology-mediated learning framework of Alavi and Leidner (2001) that posited that the internal psychological processes of learners are the mediating construct that directly affects learning outcomes. The psychological processes are influenced by information technology and instructional strategies in a given instructional context.

**Research Model and Hypotheses**

The model in Figure 1 represents the relationships among four constructs. The two independent constructs are self-efficacy (selfeff) and self-managed/regulated learning (selfRL). The dependent construct is e-learning system effectiveness (sysfEffec) and user satisfaction with LMS (satisfac). This research model differs from a prior similar study (Eom 2012) in that it has only two independent constructs while the prior study includes two more independent constructs (system quality and information quality). Besides, with additional evidence from the literature (Sharma et al. 2007), this model attempts to test relationship between computer self-efficacy and e-learner's self-regulation.
Self-efficacy is an individual’s belief and confidence in his or her ability to accomplish a certain task and to produce designated levels of performance with the skills he or she has (Bandura, 1986; Bandura, 1991). Self-efficacy beliefs determine how people motivate themselves and behave (Bandura 1994). The original concept of self-efficacy is defined broadly as an individual’s belief/judgments/perceptions of his or her abilities to use skills/artifacts including computers and information technologies. Later management information systems (MIS) researchers introduced the term, computer self-efficacy as an important MIS research construct. Compeau and Higgins (1995) defined it as “an individual's perception of his or her abilities to use computers in the accomplishments of a task.”

Computer self-efficacy was positively linked to e-learning outcomes measured by average test scores in e-learning (Simmering et al. 2009). Johnson, Hornik and Salas (2008) found that e-learners’ self-efficacy and perceived usefulness of the system were positively related perceived content value, course satisfaction, and course performance. Other studies have examined attitudes and behaviors influencing course management system usage. Significant positive relationships were found between self-efficacy and e-learning system use intention. Computer self-efficacy, attainment value, utility value, and intrinsic value were significant predictors of individuals’ intentions to continue using Web-based learning(Chiu et al. 2008). Significant positive correlations were also found between self-efficacy and e-learner satisfaction (Liaw et al. 2013). Therefore, we hypothesize the following.

\[ H_1: \] Computer self-efficacy will be positively related to e-learner satisfaction with LMS.
\[ H_2: \] Computer self-efficacy will be positively related to the effectiveness of LMS.

Self-efficacy and Self-regulation

Some research perceives self-efficacy as an essential factor to increase learners’ self-regulation in e-learning environments and therefore e-learners with higher levels of intrinsic goal orientation and e-learning self-efficacy are likely to have better e-learning course performance (Sharma et al. 2007). Other studies also suggest that e-learners with a higher level of perceived self-efficacy tend to have more positive attitudes toward learning environments, which lead to improved learning outcomes (Chu et al. 2010; Liaw 2008). Therefore, we hypothesize the following.

![Fig. 1. Research model](image-url)
H₃: Computer self-efficacy will be positively related to e-learner’s self-regulation.

**Self-regulated learning and LMS**

Self-regulation refers to self-managing behavior, motivation, and cognition (Zimmerman 1995). Numerous research studies suggest that self-regulation in distance learning may be more important than in traditional face-to-face learning because of the changing role of students from passive learners to active learners (Jonassen et al. 1995; King et al. 2000). E-learning systems placed more responsibilities on learners than traditional face-to-face learning systems. Education psychologists found that the essential qualities that discriminate a self-regulated learner from others are the individual’s conscious choice of cognitive learning strategy and learning goals, and continuous monitoring and self-assessment of learning effectiveness and progress toward the learning goals and outcome (Zimmerman 1986; Zimmerman 1989). Self-regulated learners possess three self-regulatory attributes (self-efficacy, self-awareness, and resourcefulness), which drive learners’ self-regulatory processes (attributions, goal setting, and self-monitoring). Self-regulatory attributes, especially self-efficacy, are positively related to task persistence, effective study activities, and learning outcomes (Zimmerman 1989). A prior research study also suggests that learner satisfaction is a significant predictor of learning outcomes (Eom et al. 2006). The second self-regulatory attribute, resourcefulness, refers to the ability to control physical surroundings and to seek help from social sources including persons and non-human references (Zimmerman 1989). A self-regulated learner is an active and persistent seeker of information. Therefore, we hypothesize the following:

H₄: Self-regulated learning will be positively related to e-learner satisfaction with LMS.
H₅: Self-regulated learning will be positively related to the effectiveness of LMS.

**Survey Instrument and Sample**

The survey questionnaire is selected from a multi-dimensional model for assessing e-learning systems success (ELSS) from the perspective of the e-learner developed by Wang, Wang, and Shee (2007). Based on DeLone and McLean’s (2003) updated IS success model, Wang, et al. developed and validated the ELSS model. The model conceptualized the construct of e-learning systems success, provided empirical validation of the construct and its underlying dimensionality. The survey instrument consisted of 35 items using a seven point Likert scale ranging from “strongly disagree” to “strongly agree.” In this study, all constructs are reflective constructs. The population was undergraduate and graduate students that were enrolled at least in an online course at a large university located in the Midwest United States. Invitations to reply to the survey were administered online at the time of log-in to 2,156 unique students. Of those students invited, 809 students volunteered responses with 674 surveys being complete and usable for a response rate of 31.3%. The 674 sample consists of 140 business students and 534 non-business students.

**Measurement Model Estimation and Validation**

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. 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). 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. Most of the loadings were above 0.8 for the five constructs, higher than the threshold value .7.

All reliability measures were above the recommended level of 0.70, thus indicating adequate internal consistency (Bernstein 1994; Fornell et al. 1982). The average variance extracted scores (AVE) were also above the minimum threshold of 0.5 (Chin 1998; Fornell et al. 1981) and ranged from 0.743 to 0.920. 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.

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)

**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 were above 0.8 for the six constructs, 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 et al. 1981). All constructs in the estimated model fulfilled the condition of discriminant validity (see Table 1).

**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 et al. 1982). The average variance extracted scores (AVE) were also above the minimum threshold of 0.5 (Chin 1998; Fornell et al. 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.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>FACTOR LOADING</th>
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<tbody>
<tr>
<td>Self-efficacy (Cronbach’s alpha = 0.882, AVE = 0.809)</td>
<td></td>
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<tr>
<td>Q29. I feel confident using a web browser.</td>
<td>0.921</td>
</tr>
<tr>
<td>Q30. I feel confident taking online tests or quizzes.</td>
<td>0.863</td>
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<tr>
<td>Q31. I feel confident uploading/downloading files.</td>
<td>0.914</td>
</tr>
<tr>
<td><strong>Self-managed learning (Cronbach’s alpha =0.920 , AVE = 0.807)</strong></td>
<td></td>
</tr>
<tr>
<td>Q25. When it comes to learning and studying, I am a self-directed person.</td>
<td>0.861</td>
</tr>
<tr>
<td>Q26. In my studies, I am self-disciplined and find it easy to set aside reading and homework</td>
<td>0.923</td>
</tr>
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time.

<table>
<thead>
<tr>
<th>Question</th>
<th>Cronbach's Alpha</th>
<th>AVE</th>
</tr>
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<tbody>
<tr>
<td>Q27. I am able to manage my study time effectively and easily complete assignments on time.</td>
<td>0.913</td>
<td></td>
</tr>
<tr>
<td>Q28. In my studies, I set goals and have a high degree of initiative.</td>
<td>0.895</td>
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**User satisfaction (Cronbach’s alpha =0.805, AVE =.727)**

<table>
<thead>
<tr>
<th>Question</th>
<th>Cronbach's Alpha</th>
<th>AVE</th>
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<tbody>
<tr>
<td>Q12. I depend upon the system.</td>
<td>0.695</td>
<td></td>
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<tr>
<td>Q15. I think the system is very helpful.</td>
<td>0.929</td>
<td></td>
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<tr>
<td>Q16. Overall, I am satisfied with the system.</td>
<td>0.915</td>
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**System effectiveness (Cronbach’s alpha =0.950 , AVE = 0.870)**

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<thead>
<tr>
<th>Question</th>
<th>Cronbach's Alpha</th>
<th>AVE</th>
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<tr>
<td>Q17. The system has a positive impact on my learning</td>
<td>0.932</td>
<td></td>
</tr>
<tr>
<td>Q18. Overall, the performance of the system is good</td>
<td>0.950</td>
<td></td>
</tr>
<tr>
<td>Q19. Overall, the system is successful.</td>
<td>0.952</td>
<td></td>
</tr>
<tr>
<td>Q20. The system is an important and valuable aid to me in the performance of my class work</td>
<td>0.895</td>
<td></td>
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| Table 1. Validity and reliability of the model constructs |

**Structural Model Results**

Unlike LISREL and other covariance structure analysis modelling approaches, which seek to reproduce as closely as possible the observed covariance matrix, the primary objective of PLS is to minimize errors (or equivalently the maximization of variance explained) in all endogenous constructs. 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. The t-statistics were estimated using the bootstrap resampling procedure (100 resamples). The results of the structural model are summarized in figure 2.

**R-Square for Dependent Constructs**

The results show that the structural model explains 30.0 percent of the variance in the user satisfaction construct, and 30.0 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 et al. 1992).

**Structural Path Coefficients**

As can be seen from the results, of the two antecedent constructs hypothesized to affect user satisfaction with LMS and LMS effectiveness, all of them are significant, suggesting that both learner’s psychological variables (self-efficacy) and psychological learning process (self-regulated learning management) show positive relationships with e-learner satisfaction with LMS and the effectiveness of LMS. Furthermore, we found that computer self-efficacy affects significantly and positively the level of e-learner’s self-regulation. The results underlines the important roles of student’s self-efficacy in the e-learning process. It suggests that self-efficacy of the students and students’ self-managed learning philosophy affects the perceived use of e-learning systems positively.
Conclusion

Contrary to other research finding (Eom 2012) which reported no significant relationships between user satisfaction and self-efficacy and between user satisfaction and self-managed learning, our findings strongly support that both learner's psychological variables (self-efficacy) and psychological learning process (self-regulated learning management) show positive relationships with e-learner satisfaction with LMS and the effectiveness of LMS. A possible reason for this aberration is due to different sample sizes and areas of study between the two. This study is based on sample size of 674 students with business and non-business majors and the previous study is based on 140 samples with only business major students.

Statistically significant evidence is found to suggest students' psychological variables (e.g., self-efficacy) and psychological learning process (e.g., self-regulated learning management) have effects on student satisfaction with LMS. This is in accordance with a prior research which found a positive relationship between student motivation, core of self-regulated learning, and on-line course satisfaction (Eom et al. 2006).

Finally, this study made a new contribution to e-learning literature by providing new empirical evidence that e-learners' self-self-efficacy has a strong positive relationship with a higher level of e-learners' self-regulated learning management.

A recently study from the University of California Davis found that first-time students in community colleges in California have, on average, a lower course completion rates between the school years of 2008-2009 and 2011-2012 (Schaffhauser 2015). This is a core issue in online learning. There is no simple solution to this problem. It was suggested that students' interaction and time management strategies must be an integral part of course policy. In addition, the readiness for online learning is an important factor that contributes toward successful completion and better learning outcomes. Self-efficacy and technical competency are an essential part of the students' readiness for online learning. The results of this study have significant implications for the distance educators, students, and administrators. Online readiness assessment can be used to give feedbacks to students who want to take online courses.
REFERENCES


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