20115th International Conference on Distance Learning and Education
IPCSIT vol.12 (2011) © (2011) IACSIT Press, Singapore

Impact of Individual Trait, Achievement Goal and Learning Stress on Learning Strategies: A Study in Educational Computer Game-Based Learning

Shu-Ning Liu [1+] and Andrea Lee [2]

[1] Department of Marketing & Distribution Management,
Hsiuping Institute of Technology, Taichung, Taiwan

[2] Department of Business Administration
National Chin-yi University of Technology, Taichung, Taiwan

Abstract. The purpose of this research was to study how individual trait, playfulness and anxiety, affect learning strategies through the mediate of good-achievement-goal and bad-learning-stress in a computer game-based learning environment. A sample of 141 Year-3 students of university participated in the study. A structural equation model showed that (1) playfulness trait have an indirect positive effect, mediated through good-achievement-goal on deep learning, (2) playfulness trait have an indirect negative effect, mediated through good-achievement-goal on surface learning, (3) anxiety trait have an indirect positive effect, mediated through bad-learning-stress on surface learning.

Keywords: playfulness, anxiety, achievement goal, learning stress, learning strategy

1. Introduction

In recent years, the collaborative educational online games have been increasingly used in Taiwan higher education institutions. Some educational scholars argued that educational computer game can stimulate players' learning motivation [18]. Nevertheless, whether this teaching method all does have the same process to the different individual trait's learners, is not been discussion in past researches.

The purpose of this research was to study how individual trait, playfulness and anxiety, affect learning strategies through the mediate of good-achievement-goal and bad-learning-stress in a computer game-based learning environment. To explore the different learn process of different individual trait's learners in educational computer game-based learning environment.

2. Literature Review and Hypotheses

2.1. Individual trait and learning strategies

Learning strategies refer to the activities by which learning is achieved. Hoeksema[13] proposed two types of learning strategies: deep and surface. A deep learning strategy is directed at understanding the meaning of a task and to satisfy curiosity. It may be considered the highest form of learning. A surface learning strategy is directed to memorizing facts, disjointed pieces of data, examples and illustrations [13]. Deep learning strategy are typically regarded to be a more adaptive way that bring students to higher achievement outcomes, whereas surface learning strategies are a less desirable form of learning process that bring a lower level of academic performance [9]. The research of Liem, Lau, & Nie[1] reproved deep learning strategy have a positive effect on achievement outcome, on the other hand, surface learning strategy have a negative effect on achievement outcome. So, the educators hope to bring out the deep learning behavior of students in learning process.

+ Corresponding author. Tel.: + 886-4-24961100#2200; fax: +886-4-22513289
E-mail address: lioushuning@yahoo.com.tw

Lieberman[11] firstly identified five components of playfulness: physical spontaneity, social spontaneity, cognitive spontaneity, manifest joy, and sense of humor. The study of Tan, & McWilliam[12] indicated the importance of playfulness as a learning disposition that mobilizes productive engagement with new learning innovations. Individuals who are experiencing playfulness are likely to interpret their feeling as signaling high intrinsic motivation and learning disposition. As a result, playfulness individuals are likely to bring an explicit goal of satisfy curiosity to learning strategy, his (or her) progressive views made him (or her) to choose the deep learning strategy, not surface learning strategy.

In contrast, the distinct meaning structure underlying anxiety is defined by high uncertainty over an outcome and low control over a situation, is generally experienced in response to situational where the person is uncertain about an impending outcome of a personally relevant event[14]. Thus, individuals who are experiencing anxiety are likely to interpret their feeling as signaling high uncertainty and lack of control [15]. As a result, anxious individuals are likely to bring an implicit goal of uncertainty reduction and risk avoidance to learning strategy, his (or her) conservative views made him (or her) to choose the surface learning strategy, not deep learning strategy.

2.2. The mediating role of achievement goal and learning stress

Accumulating evidence in the achievement goal literature has established a consistent pattern that mastery and performance-approach goal would facilitate the use of deep learning strategies [2] [4] [1]. Mastery and performance-approach goal have highly positive correlation, both can generate adaptive achievement outcome.

LePine, Lepine, & Jackson[8] proposed that both forms of stress lead to effect motivation to learning. Challenge stress, good-learning-stress, is associated with high motivation to learn and the other form of hindrance stress, bad-learning-stress, is associated with low motivation to learn. The transactional theory [17] suggests that after a stressful situation is appraised as being a hindrance or a challenge, secondary appraisals assess how to cope. If the stress reflects a situation appraised as being potentially negative and uncontrollable, however, a cognitive style of withdrawing from the situation by wishing it would go away.

Because playfulness learners have high intrinsic motivation and learning disposition that mobilizes achievement pursuance with new learning innovations, on the contrary, anxiety learners have high risk avoidance that feels hindrance stress with new learning innovations, therefore, we hypothesize:

H_1: Playfulness trait will have an indirect positive effect, mediated through good-achievement-goal on deep learning.

H_2: Playfulness trait will have an indirect negative effect, mediated through good-achievement-goal on surface learning.

H_3: Anxiety trait will have an indirect negative effect, mediated through bad-learning-stress on deep learning.

H_4: Anxiety trait will have an indirect positive effect, mediated through bad-learning-stress on surface learning.

3. Methodology

3.1. Participants and procedures

The subjects for this study were 3-class, 141-student enrolled in a 8-week marketing simulation decision course. The course used marketing-winner simulation system to proceed computer game-based teaching, and included 6-unit marketing. Marketing-winner Simulation System is a Web-based portfolio management game, the contest modules cover two markets, three products, six management strategies and product information. First, the 141-student had to finish their “Playfulness and anxiety trait scale” before course. Second, the same teacher, course unit, teaching method and teaching schedule had been used to 3-class. Through 8-week, the 141-student then finished 3 subscales included “good-achievement-goal”, “bad-learning-stress”, and “learning strategy”.

3.2. Measures

● Individual Trait

The 29-item playfulness trait subscale of six factors was used [15]. Participants indicated the extent to which they thought each item was true of them on a 1 (never true of me) to 5 (always true of me) scale. The

20-item anxiety trait subscale was used [5]. Participants indicated the extent to which they thought each item was true of them on a 1 (never) to 4 (almost always) scale.

● Good-achievement-goal

The 6-item good-achievement-goal subscale was used [3]. Two types of good-achievement-goal, master approach and performance approach, were measured in this study. Participants indicated the extent to which they thought each item was true of them on a 1 (not at all true of me) to 7 (very true of me) scale.

● Bad-learning-stress

The 5-item bad-learning-stress (hindrance stress) subscale of the Leptine, Leptine, & Jackson [8] developed was used. Two types of learning stresses were measured in their study. In the present study, hindrance stress was been used to measure bad-learning-stress linked to busy work and hassles. Participants indicated the amount of stress the circumstance in the item produced on a 5-point scale (ranging from 1 no stress to 5 a great deal of stress).

● Learning strategy

The 20-item learning strategies subscale of the R-SPQ-2F-questionnaire was used [10]. Two types of learning strategies, surface learning and deep learning, were measured in this study. Participants indicated the extent to which they thought each item was true of them on a 1 (never true of me) to 5 (always true of me) scale.

● Item-Parcel confirmatory factor analysis

Before the proposed model was tested, a measurement model of the six latent variables was checked. However, when conducting overall confirmatory factor analysis, the excess of original items might create underestimate of model fitness [7]. To reduce this problem, this study used item-parcel confirmatory factor analysis to reduce the number of observed items as suggested by Espelage et al. [6]. For each of the six latent variables, single items were randomly assigned into two parcels. Two item parcels were subsequently created for each latent variable. Mean scores were calculated for each item parcel (Table I).

For the six-factor model, each item parcel was constrained to load on its respective subscale. Through an item-parcel confirmatory factor analysis, the item-parcels for each subscale were examined for convergent validity and construct validity. All of the t-values of item-parcels showed statistical significance at the .05 level, indicating that all of those item-parcels within each subscale were highly correlated and, therefore, revealed convergent validity. In addition, construct validity was established by examining the extracted variance of each subscale by the factor analysis. It was found that the item-parcels representing each subscale accounted for between 45% and 79% of variance. The reliability of the subscale was demonstrated by examining the composite reliability coefficient. Shown in table I, all of these coefficients were over .60. Therefore, the instrument reliability was established. In sum, the results from table I demonstrate the high validity and reliability of the instrument, and the measurement model yielded an acceptable level of fit.

Table 1: Item parcels for confirmatory factor analysis

Subscale	Item-parcel(Item No.)	Factor loading	Average variance extracted	Composite reliability	α
Playfulness Trait	PT1(1,2,3,4,5,6,7,8,9,10,11,17,18,19,20,21)	.94	.79	.88	.93
	PT2(12,13,14,15,16,22,23,24,25,26,27,28,29)	.83			
Anxiety Trait	AT1(1,2,4,8,11,12,17,18,20)	.81	.74	.85	.84
	AT2(3,5,9,10,15,16,19)	.91			
Good-achievement-goal	GO1 (1,2,3)	.81	.45	.60	.85
	GO2 (4,5,6)	.49			
Bad-learning-stress	SO1 (3,5)	.80	.65	.79	.77
	SO2 (1,2,4)	.81			
Deep Learning	DL1 (1,2,14,17,18)	.86	.79	.88	.90
	DL2 (5,6,9,10,13)	.92			
Surface Learning	SL1 (4,8,11,15)	.70	.64	.78	.77
	SL2 (3,12,16,19)	.89			

Note：$\chi2$ =47.85, df =39, $\chi2$/df =1.23, RMSEA=.04, GFI =.95, NFI=.93, IFI=.99, TLI=.98, CFI=.99

● Analysis

Then, this study conducted the structural equation model to test our hypotheses. Since ther were several observed variables, the fitness of the model could be underestimated [16]. To reduce this problem, the study employed the item-parcels previously used in the confirmatory factor analysis in order to reduce the numbers of observed variables. The six variables were reduced to 2 new predictor variables respectively that were used in the subsequent analysis.

4. Results and Conclusion

4.1. Testing the Model and Results of SEM analysis

The structural equation model was conducted using the AMOS 18.0 program. For the six variables data was all collected by self-report instruments, it is likely that this research suffers a methodological problem termed common method variance (CMV). CMV will inadequately inflate or deflate the relationship between variables, resulting in an increase of statistical significance. This research used a statistical technique - controlling for the effects of a single unmeasured latent method factor - to avoid the problem. Table II presents the path coefficients and their significance levels between predictors and criteria variables in the theory models of pre-control CMV and post-control CMV. The path coefficients have no significant difference between the pre-control CMV model and post-control CMV model. It exhibits the significant effects between predictors and criteria variables in this study were not inadequately inflate or deflate by CMV. In order to strive for the simplification, we used the post-control CMV model denoted the hypotheses (See Fig. I).

Table 2: Standardized path coefficients and significance levels in the model

Path	pre-control CMV model		post-control CMV model	
Playfulness Trait → Deep Learning	.21*	(2.09)	.13	(1.13)
Playfulness Trait → Surface Learning	$.20^{+}$	(1.74)	.16	(1.64)
Playfulness Trait → Good-achievement-goal	.36**	(3.00)	.34**	(2.46)
Playfulness Trait → Bad-learning-stress	.11	(1.09)	.17	(1.50)
Anxiety Trait → Deep Learning	.15	(1.61)	.16	(1.62)
Anxiety Trait → Surface Learning	- .01	(- .05)	-.01	(- .13)
Anxiety Trait → Good-achievement-goal	-. 13	(-1.06)	-.13	(-1.12)
Anxiety Trait → Bad-learning-stress	.27*	(2.39)	$.20^{+}$	(1.86)
Good-achievement-goal → Deep Learning	.72***	(4.64)	.76***	(4.70)
Good-achievement-goal → Surface Learning	-. 59***	(-3.68)	-.61***	(-3.52)
Bad-learning-stress → Deep Learning	-. 15^{+}	(-1.73)	-.10	(- .97)
Bad-learning-stress → Surface Learning	.28*	(2.42)	.27*	(2.25)
Playfulness ↔ Anxiety Trait	-.28**	(-2.57)	-.27**	(-2.25)

Note: () t-value

The results presented in fig. I showed that the playfulness trait had significantly positive effects on good-achievement-goal (β= .34, p<.05). Good-achievement-goal had a significantly positive effect on deep-learning (β= .76, p<.001), and a significantly negative effect on surface-learning (β= -.61, p < .001). Therefore, good-achievement-goal had a full mediating effect on the relationship between playfulness trait and deep learning, and between playfulness trait and surface learning.

Anxiety trait had significantly positive effects on bad-learning-stress (β= .20, p<.1), and bad-learning-stress had a significantly positive effects on surface learning (β= .27, p<.05). Therefore, bad-learning-stress had a full mediating effect on the relationship between anxiety trait and surface learning.

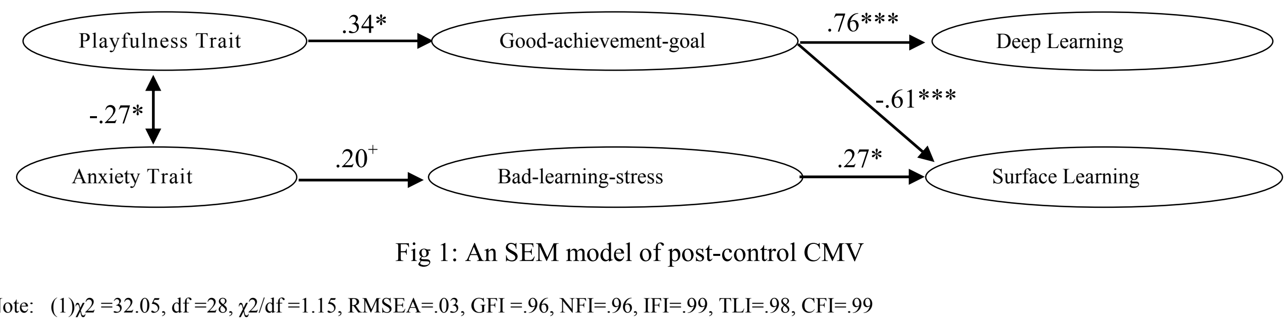

Fig 1: An SEM model of post-control CMV

Note: (1)$\chi 2$ =32.05, df =28, $\chi 2$/df =1.15, RMSEA=.03, GFI =.96, NFI=.96, IFI=.99, TLI=.98, CFI=.99

(2) + p< .1, *p< .05, **p< .01, ***p< .001

4.2. Conclusion

In recent years, the collaborative educational online games have been increasingly used in Taiwan higher education institutions. This study had proved that the different individual trait's learners had different learning process in the learning situation of educational computer game-based. Learning strategy plays a critical role in predicting and determining a learner's academic performance [9]. The high playfulness trait learners, through satisfy achievement goal, choose the deep learning strategy that the educators hope to bring out. The high anxiety trait learners, through mobilize learning-stress, choose the surface learning strategy that a less desirable form of learning process. Therefore, the findings of our study could be useful in designing educational computer game-based learning environment.

5. Acknowledgements

This study was supported by the National Science Council of Taiwan (NSC 97-2511-S-164 -003 -MY3)

6. References

[1] A.D. Liem, S. Lau, and Y, Nie. The role of self-efficacy, task value, and achievement goals in predicting learning strategies, task disengagement, peer relationship and English achievement outcome. *Contemporary Educational Psychology*. 2008, **33**(4): 486-512.

[2] A.J. Elliot, and H. McGregor. A 2 x 2 achievement goal framework. *Journal of Personality and Social Psychology*. 2001, **80**(3): 501-519.

[3] A.J. Elliot, and K. Murayama, On the measurement of achievement goals: critique, illustration, and application. *Journal of Educational Psychology*, 2008, **100**(3): 613-628.

[4] B.A. Greene, R.B. Miller, H.M. Crowson, B.L. Duke, and K.L. Akey, Predicting high school students' cognitive engagement and achievement: Contributions of classroom perceptions and motivation. *Contemporary Educational Psychology*, 2004, **29**: 462-482.

[5] C.D. Spielberger, *Manual for the State-Trait Anxiety Inventory(Form Y)*. Palo Alto, CA: Consulting Psychologists Press, 1983.

[6] D.L. Espelage, S.E. Mazzeo, S.H. Aggen, A.L. Quittner, R. Sherman, and R. Thompson. Examining the construct validity of the eating disorder inventory. *Psychological Assessment*. 2003, **15**(1): 71-80.

[7] F. Nasser, and T. Takahashi. The effect of using item parcels on ad hoc goodness-of-fit indexes in confirmatory factor analysis: An example using Sarason's RTT. *Applied Measurement in Education*. 2003, **16**: 75–97.

[8] J.A. LePine, M.A., LePine, and C.L. Jackson. Challenge and hindrance stress: Relationships with exhaustion, motivation to learn, and learning performance. *Journal of Applied Psychology*. 2004, **89**(5): 883–891.

[9] J.B. Biggs. *Student Approaches to Learning and Studying*. Melbourne: Australian Council for Educational Research. 1987.

[10] J.B. Biggs, D. Kember, and D.Y.P. Leung, The revised two-factor stud process questionnaire: R-SPQ-2F. *British Journal of Educational Psychology*, 2001, **71**: 133-149.

[11] J.N. Lieberman, Playfulness and divergent thinking: an investigation of their relationship at the kindergarten level. *Journal of Genetic Psychology*, 1965, **107**: 219-224.

[12] J. Pei-Ling. Tan, and E.L. McWilliam, Cognitive playfulness, Creative Capacity and Generation 'C' Learners. In: *Proceedings of Creating Value between Commerce and Common's Conference*, 2008, June 25-27, Brisbane, Australia.

[13] L.H. Hoeksema. *Learning Strategy as a Guide to Career Success in Organizations*. The Netherlands: DSWO Press, 1995.

[14] N.H. Frijda, P. Kuipers, and E. Shure, Relations among emotion appraisal and emotional action readiness. *Journal of Personality and Social Psychology*, 1989, **57**: 212–228.

[15] P. Yu, J.J. Wu, W.W. Lin, and C.H. Yang, The development of adult playfulness scale and organizational playfulness climate questionnaire. *Psychological Testing*, 2003, **50**(1): 73-110.

[16] P.M. Bentler, and C.P. Chou. Practical issues in structural modeling. *Sociological Methods and Research*. 1987, **17**: 78-117.

[17] S. Folkman, and R.S. Lazarus. *Stress, Appraisal, and Coping*. New York : Springer Publishing Company, 1984.

[18] S. Terrell and P. Rendulic. Using computer-managed instructional software to increase motivation and achievement in elementary school children. *Journal of Research on Computing in Education*. 1996, **26**(3): 403-414.