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## The Relationship of Kolb Learning Styles, Online Learning Behaviors and Learning Outcomes

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### ABSTRACT

This study focused on the relationship between Kolb learning styles and the enduring time of online learning behaviors, the relationship between Kolb learning styles and learning outcomes and the relationship between learning outcomes and the enduring time of a variety of different online learning behaviors. Prior to the experiment, 104 students majoring in Educational Technology completed Kolb's Learning Style Inventory (KLSI). Forty students were chosen to be subjects in an online learning experiment. Results indicated that there was a significant effect of Kolb learning style on the total reading time and total discussion time of the subjects. Although there was no significant effect between Kolb learning styles and learning outcomes, data from the experiment showed that the mean of learning outcomes of Convergers and Assimilators was higher than that of Divergers and Accommodators. There were two models of linear regression between learning outcomes and the enduring time of different online learning behaviors. Both of them were significant at the 0.001 level, and they accounted for 54.9% and 60.8% of the variance of the dependent respectively. The findings of this study were instrumental to instructors and moderators of online courses. First, instructors using online courses should seriously consider the diversity of learning styles when designing and developing online learning modules for different students. Second, they should provide a large number of electronic documents for students and give enough time to let them absorb knowledge by online reading. These could be effective methods to improve the quality of online courses.

### Keywords

Kolb learning styles, Online learning behaviors, Learning outcomes

### Introduction

Although online learning was growing rapidly, the effect of it was not yet satisfactory. For example, some students often complained that they could not find sufficient online learning resources to support their online courses, whereas other students were restricted by what they felt as a lack of opportunities to communicate with their instructors (Huang, 2003). Leigle & Janicki (2006) offered solutions to these problems, arguing that by customizing learning modules for differing student types, the learning outcome would be increased. Based upon this solution, the present study focused on the relationship of Kolb learning styles, online learning behaviors and learning outcomes. It was hoped that this study could help instructors understand the function of learning style in an online learning environment and thus develop corresponding online learning modules for different students.

### Kolb Learning Style Model

The Kolb learning style model was based on Kolb's experiential learning theory. In this model, Kolb defined learning style on a two-dimensional scale based on how a person perceived and processed information. How a person perceived information was classified as concrete experience or abstract conceptualization, and how a person

processed information was classified as active experimentation or reflective observation (Simpson & Du, 2004). Accordingly, Kolb (1985) described the process of experiential learning as a four-stage cycle involving four adaptive learning modes: Concrete Experience (CE), Reflective Observation (RO), Abstract Conceptualization (AC), and Active Experimentation (AE). CE tended towards peer orientation and benefited most from discussion with fellow CE learners. AC tended to be oriented more towards symbols and learned best in authority-directed, impersonal learning situations, which emphasized theory and systematic analysis. AE tended to be an active, “doing” orientation to learning that relied heavily on experimentation and learned best while engaging in projects. RO relied heavily on careful observation in making judgments. Kolb (1985) also identified four learning style groups based on the four learning modes: Divergers favored CE and RO, Assimilators favored AC and RO, Convergents favored AC and AE, and Accommodators favored CE and AE.

### **Kolb Learning Style Inventory**

There were many different learning style models. Many of them were derived from a common ancestry and measured similar dimensions (Brown, 2005). Accompanied by a vast collection of learning models, there was also a wealth of confusing assessment tools, amongst which, Kolb Learning Style Inventory (KLSI) remained one of the most influential and widely distributed instruments used to measure individual learning preference (Kayes, 2005). The original KLSI encountered serious attacks because of its low test-retest reliability and limited construct validity (John et al., 1991). In 1985, Kolb and his associates revised the KLSI to improve and refine its psychometric properties (Smith & Kolb, 1986).

Some researchers had examined and found support for the revised KLSI. Veres et al. (1991) examined the revised KLSI and found increased stability. They argued that the revised KLSI might well be useful to researchers, educators and practitioners. Raschick, Maypole & Day’s (1998) research found the revised KLSI a useful tool for optimizing the relationship between supervisors and their students. The tool enabled both groups to view learning as a four-step process that involved experiencing, reflecting, conceptualizing and creatively experimenting. Based on these favorable results, KLSI became a well-accepted instrument for this experiment.

### **Review of Literature**

Some recent studies analyzed the online learning behaviors between Kolb learning style groups. Simpson & Du (2004) explored the effect of Kolb learning styles on students’ online participation and self-reported enjoyment levels in distributed learning environments. Multiple regression analysis found that learning style had a significant impact on the students’ participation and enjoyment level. Fahy (2005) conducted a study of the relations between Kolb learning style and online communication behavior, and found that Convergents demonstrated their willingness to spend more time and energy on the network itself. Liegle & Janicki (2006) found that learners classified as “Explorers” (Active experimenters) tended to create their own path of learning (learner control), while subjects classified as “Observers” (Reflective observers) tended to follow the suggested path by clicking on the “Next” button (system control) in a web-based training program. However, there were studies that reached opposite conclusions. For example, in the environment of hypermedia learning, Reed et al. (2000) argued that Kolb learning styles had no effect on the number of linear steps, which determined whether the steps were the next logical, sequentially forward movement, and on the number of nonlinear steps, which determined whether the steps were branches or sidetracks. Why did inconsistent results occur in above-mentioned studies? The answer was that the lack of effect of Kolb learning styles could be due to that those studies involved the research variables, such as linear steps vs. nonlinear steps, that Kolb instrument did not seem to measure (Miller, 2005). According to the view, if research variables of the experiment could be measured by the KLSI, the effect of Kolb learning style would appear. To test it, this study chose for the online learning behaviors related with KLSI to be researching variables.

Research investigating the learning outcome in an online or a hypermedia environment also reached confusing conclusions. For instance, Melara (1996) examined the effect of Kolb learning styles on learner performance within two different hypertext structures, and showed no significant difference in achievement for learners of different learning style using either hypertext structure. Davidson-shivers et al. (2002) investigated the effect of Kolb learning styles on undergraduate writing performance in a multimedia lesson. No statistically significant difference in writing performance among the learning styles was found. Howard and colleagues (2004) argued that, even though

significant learning occurred, no significant difference in achievement was observed within any Kolb's classifications. Miller (2005) found no effect of Kolb learning styles on performance when using a computer-based instruction system to teach introductory probability and statistics. Some experiments, however, showed positive effects of Kolb learning styles on students' performance. Oughton & Reed (2000) tested 21 graduate students enrolled in a graduate hypermedia education class. They were told to construct concept maps on the term of hypermedia. Findings indicated that Assimilators and Divergers were the most productive on their concept maps. Terrell (2002) indicated that, in a web-based learning environment, students whose learning styles belonged to Convergers and Assimilators were likely to succeed than students whose learning styles belonged to Divergers and Accommodators. These confusing conclusions might be produced by various factors, such as the topic of the course and how grades are given. Therefore, practitioners of online courses had to take these factors into consideration when they hoped to make use of relevant research conclusions.

Most of the previous research focused on investigating either online learning behavior or the learning outcome between Kolb learning style groups. Little research dealt with the relationship between online learning behavior and learning outcome. The purpose of this study was to prove if there were differences in the online learning behavior between Kolb learning style groups, and if so, whether the differences would lead to differences in the learning outcome.

## **Research Variables**

### *Kolb Learning Style Groups*

The KLSI could identify subjects' preference for perceiving and processing information. Subjects responded to the 12-item Kolb instrument and were categorized as Convergers, Divergers, Assimilators or Accommodators.

### *Online Learning Behavior*

Corresponding with the four learning modes in the Kolb learning style model, four different online learning behaviors were identified as research variables in this study. The enduring time of these variables was measured when the subjects designed Flash animations in an online learning environment. These types of behavior involved online discussion preferred by CE, online reading of electronic documents preferred by AC, Flash animation designing preferred by AE, and online observation of onscreen activities of other subjects preferred by RO.

### *Learning Outcome*

The subjects' task was to design one animation using Flash software. The animation included ten different text effects. Each effect of the animation counted as one point for a total of ten points. The learning outcome was to be measured according to the amount of text effects completed by the subjects.

## **Research Questions**

The authors of this experiment hypothesized that the subjects with different learning styles tended to choose different online learning behaviors, which would subsequently result in different learning outcomes of the subjects.

The research questions guiding this experiment were as follows: (1) What was the relationship between learning styles and the enduring time of online learning behaviors? (2) What was the relationship between learning styles and learning outcomes? (3) What was the relationship between learning outcomes and the enduring time of different online learning behaviors?

## Method

### Participants

The participants were third-year undergraduate students in the Department of Educational Technology at Shandong Normal University in China. 104 students took part in the test of KLSI, 40 of whom, demonstrating evident preferences for learning styles, were chosen as subjects, with ten subjects in each learning style category. Table 1 showed gender distributions of learning style categories.

Table 1. Gender distribution of Kolb categories

	Male	Female
Convergers	5	5
Divergers	4	6
Assimilators	5	5
Accommodators	4	6

These subjects had grasped some basic computer knowledge, such as the application of Internet, the use of communicating software, drawing software and word processing software. They also acquired basic knowledge of Flash when they were freshmen.

### Procedure

The experiment was performed in the university computer laboratory. The subjects were divided into ten groups. Each group contains four subjects including one Converger, one Diverger, one Assimilator and one Accommodator. Then they were given 120 minutes to perform the designated task. During the 120 minutes, these four subjects worked individually and each one met with one experimenter, who observed and recorded their behaviors. Four graduate students who were familiar with the application of Flash were arranged to communicate with the subjects through the instant messaging software of QQ. A website encompassing an electronic document of how to design the animation using Flash was also provided. This electronic document was a detailed guide of how to design the animation in the task.

Initially, the subjects were given 20 minutes to respond to the task. They were required to do so individually, without the help of online consultations, observations or references. After this pretest, they were given a 10-minute break. Each subject was then administered a posttest lasting 90 minutes, to respond to the task again. This time they could discuss with the graduate students through QQ, observe the designing process of other subjects (The subjects were authorized to access to the onscreen operations of others with their own computers.), read the electronic document on the Internet or design Flash animations by themselves. During the posttest, the experimenter observed and recorded the participants' enduring time in online discussion with the graduate students (total discussion time), the enduring time observing the onscreen activities of others (total observation time), the enduring time actively reading the electronic document (total reading time) and the enduring time designing Flash animations (total designing time). Data analyses were performed by using the Statistical Package for the Social Sciences, for Windows ([SPSS] ver. 13.0).

## Results

### The relationship between learning styles and the enduring time of online learning behaviors

The relationship between learning styles and the enduring time of online learning behaviors was analyzed in one-way ANOVA. The analysis found that learning styles had no significant effect on total observation time and total designing time. In fact, all subjects spent more than 45 minutes on designing. Only five subjects spent one or two minutes on observing the onscreen activities of others and the rest spent no time on the observation. However,

subjects with different learning styles demonstrated significant differences in the categories of total discussion time and total reading time.

Table 2. ANOVA for different learning styles and the enduring time of online learning behaviors

	Convergers		Divergers		Assimilators		Accommodators		F	Prob.
	M (min)	SD	M (min)	SD	M (min)	SD	M (min)	SD		
Total discussion time	7.8	3.2931	14.1	4.4083	6.4	3.3400	12.6	3.2042	10.617	<u>0.000</u>
Total observation time	0.2	0.6325	0.1	0.3162	0.3	0.6749	0.1	0.3162	0.347	0.791
Total reading time	20.9	3.9847	15.9	3.3813	21.2	2.7809	14.1	3.6652	10.525	<u>0.000</u>
Total designing time	55.1	6.7569	53.8	4.8717	56.9	5.3427	57.7	5.9451	0.929	0.437

Table 3. Scheffé post hoc comparison of total discussion time

	Convergers (Prob.)	Divergers (Prob.)	Assimilators (Prob.)	Accommodators (Prob.)
Convergers		<u>0.005</u>	0.859	<u>0.045</u>
Divergers	<u>0.005</u>		<u>0.000</u>	0.832
Assimilators	0.859	<u>0.000</u>		<u>0.006</u>
Accommodators	<u>0.045</u>	0.832	<u>0.006</u>	

Table 4. Scheffé post hoc comparison of total reading time

	Convergers (Prob.)	Divergers (Prob.)	Assimilators (Prob.)	Accommodators (Prob.)
Convergers		<u>0.027</u>	0.998	<u>0.001</u>
Divergers	<u>0.027</u>		<u>0.017</u>	0.722
Assimilators	0.998	<u>0.017</u>		<u>0.001</u>
Accommodators	<u>0.001</u>	0.722	<u>0.001</u>	

Table 3 and Table 4 (the Scheffé post hoc comparisons) showed that two significant effects appeared between the subjects who favored abstract conceptualization (Convergers and Assimilators) and those who favored concrete experience (Divergers and Accommodators). That is, on the one hand, subjects identified as Convergers and Assimilators spent more time on online reading than those identified as Divergers and Accommodators. On the other hand, subjects identified as Divergers and Accommodators spent more time on online discussing than those identified as Convergers and Assimilators. Furthermore, significant differences were not found between gender and total discussion time ( $F(1,38)=0.041$ ,  $p=0.841$ ), total observation time ( $F(1,38)=0.009$ ,  $p=0.926$ ), total reading time ( $F(1,38)=0.432$ ,  $p=0.515$ ) and total designing time ( $F(1,38)=0.009$ ,  $p=0.925$ ).

### The relationship between learning styles and learning outcomes

The subjects had learned some introductory knowledge of Flash in their first year of university. Owing to scarce practice during the following two years, only seven subjects finished one text effect in the pretest. Among them were two Convergers, one Diverger, one Assimilator and three Accommodators. No subject completed the ten effects in the posttest. The task seemed challenging to all subjects.

Table 5. Learning outcomes of different learning styles

	Convergers		Divergers		Assimilators		Accommodators	
	M	SD	M	SD	M	SD	M	SD
Pretest	0.2	0.422	0.1	0.316	0.1	0.316	0.3	0.483
Posttest	5.3	2.163	4.4	1.776	4.9	2.183	4.8	2.658
Learning outcomes	5.1	1.912	4.3	1.567	4.8	2.044	4.5	2.224

To analyze the relationship between learning styles and learning outcomes, each subject was categorized as demonstrating either a high or low learning outcome. High learning outcome was defined as a learning outcome which was equal to or more than five points (higher than the mean learning outcome for subjects, M=4.68). The result of chi-square test showed that there was no significant association between learning styles and learning outcomes ( $\chi^2(3, N=40)=2.707, p=0.538$ ), and no significant association between gender and learning outcomes ( $\chi^2(1, N=40)=0.123, p=0.726$ ).

**The relationship between learning outcomes and the enduring time of different online learning behaviors**

To answer the research question of “what was the relationship between learning outcomes and the enduring time of different online learning behaviors?”, a multiple linear regression was conducted regressing the learning outcomes on the four predictor variables (total discussion time, total observation time, total reading time and total designing time).

Table 6. Correlations between learning outcome and independent variables

Variables	Intercorrelations					M	SD
	X1	X2	X3	X4	Y		
Total discussion time (X1)	1	-0.082	-0.226	-0.624	0.319*	10.225	4.7420
Total observation time (X2)		1	0.155	-0.143	-0.127	0.175	0.5006
Total reading time (X3)			1	-0.535	0.566**	18.025	4.5825
Total designing time (X4)				1	-0.702**	55.875	5.7565
Learning outcomes (Y)					1	4.675	1.8999

\*\* . Correlation is significant at the 0.01 level (2-tailed).

\* . Correlation is significant at the 0.05 level (2-tailed).

The correlations between the dependent variable (learning outcome) and the independent variables (total discussion time, total observation time, total reading time and total designing time) were shown in Table 6. The dependent variable was significantly correlated with total designing time ( $r=-0.702, p<0.01, n=40$ ), total reading time ( $r=0.5006, p<0.01, n=40$ ) and total discussion time ( $r=0.319, p<0.05, n=40$ ). The correlation between total reading/discussion time and learning outcome was positive while the correlation between total designing time and learning outcome was negative. Such results suggested that spending too much time designing animations in an online learning environment would put a damper on learning outcome. On the other hand, reading and discussing would be conducive to learning outcome.

Table 7. Results of Multiple Regression Analysis (Model Summary)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1 <sup>a</sup>	0.741	0.549	0.512	1.3275
2 <sup>b</sup>	0.780	0.608	0.563	1.2556

a. Predictors: (Constant), total discussion time, total reading time, total designing time.

b. Predictors: (Constant), total observation time, total discussion time, total reading time, total designing time.

Table 8. Results of Multiple Regression Analysis (ANOVA)

Model		Sum of Squares	df	Mean Square	F	Prob.
1 <sup>a</sup>	Regression	77.336	3	25.779	14.629	<u>0.000</u>
	Residual	63.439	36	1.762		

	Total	140.775	39			
2 <sup>b</sup>	Regression	85.594	4	21.398	13.572	<u>0.000</u>
	Residual	55.181	35	1.577		
	Total	140.775	39			

a. Predictors: (Constant), total discussion time, total reading time, total designing time. Dependent Variable: learning outcome.

b. Predictors: (Constant), total observing time, total discussion time, total reading time, total designing time. Dependent Variable: learning outcome.

Table 9. Results of Multiple Regression Analysis (Coefficients)

Model <sup>a</sup>		Unstandardized Coefficients		Standardized Coefficients	t	Prob.
		B	Std. Error	Beta		
1	(Constant)	7.953	8.461		0.940	0.354
	Total discussion time	0.069	0.108	0.173	0.641	0.525
	Total reading time	0.167	0.103	0.402	1.612	0.116
	Total designing time	-0.125	0.103	-0.379	-1.219	0.231
2	(Constant)	13.092	8.312		1.575	0.124
	Total discussion time	0.004	0.106	0.009	0.035	0.972
	Total observing time	-0.969	0.423	-0.255	-2.289	<u>0.028</u>
	Total reading time	0.125	0.100	0.302	1.257	0.217
	Total designing time	-0.189	0.101	-0.572	-1.868	0.070

a. Dependent Variable: learning outcome.

Findings from the multiple regression analysis were summarized in Table 7, 8 and 9. The linear regression analysis encompassed the individual-level variables of the subject's learning outcome, total discussion time, total observation time, total reading time and total designing time. Of course, there was a precondition for model 1 and 2, that is, all subjects spent more than half of the total time on designing. In the first step of the analysis (Model 1), the simultaneous entry was specified for total discussion time, total reading time and total designing time. From table 7, we could find that model 1 accounted for 54.9% ( $R^2=0.549$ ) of the variance, which was significant at the 0.001 level. In the second step (Model 2), total observation time was added. It increased the  $R^2$  by 5.9%. In table 8, the value of F was the mean square regression divided by mean square residual. The probability of the F-values in two models showed that the likelihood of the given correlation occurring by chance was less than 1 in 10,000. It meant that both linear regression equations were significant. In table 9, the values of B were the coefficients and constant of the linear regression equation. Beta was the B-value for standardized scores of the independent variables. The Beta-values indicated the relative influence of the independent variables to dependent variable. From table 9, we could find that, in model 1, total reading time and total discussion time had positive influence, while total designing time had negative influence. In model 2, total reading time and total discussion time had positive influence, while total designing time and total observation time had negative influence.

## Discussion

This study explored a new and important issue on the relationship of Kolb learning styles, online learning behaviors and learning outcomes. It highlighted the emergent themes in following areas. Firstly, there was a significant effect of learning styles on total reading time and total discussion time. Convergers and Assimilators spent more time on online reading than Divergers and Accommodators, while Divergers and Accommodators spent more time on online discussing than Convergers and Assimilators. The findings were found to be theoretically consistent with the predictions of the Kolb learning style model. Convergers and Assimilators possessed the character of Abstract Conceptualization (AC). One with a high score in AC indicated that s/he was more oriented towards symbols and learned best in authority-directed, impersonal learning situations (Kolb, 1985). Therefore, s/he tended to read the electronic document of how to design the animation in the experiment. Divergers and Accommodators possessed the character of Concrete Experience (CE). One with a high score in CE indicated that s/he was more oriented towards



peers and benefited most from discussions. Therefore, s/he tended to discuss with the graduate students who acted as online consultants in the experiment.

Secondly, learning styles had no significant effect on learning outcomes. This experiment result was not anticipated by the researchers. However, Table 5 showed that the mean of learning outcomes of Convergers and Assimilators was higher than that of Divergers and Accommodators, which was in accordance with some previous conclusions. For example, Terrell (1995) predicted that students taking computer-mediated coursework would primarily be Convergers and Assimilators. Henke (2001) postulated that Assimilators and Convergers might be more successful to computer-based trainings than other students with different learning styles. In fact, same conclusion could also be drawn from the linear regression between learning outcome and the enduring time of different online learning behaviors. In the full model, total designing time, total reading time and total discussion time were significantly related to learning outcomes. Table 9 showed that either in model 1 or model 2, the standardized regression coefficient of total reading time was larger than the standardized regression coefficient of total discussion time. This meant that the influence of total reading time on learning outcomes was larger than the influence of total discussion time. Therefore, students who spent more time on online reading could get better learning outcomes than students who spent more time on online discussions. It explained the reason why the mean of learning outcomes of Convergers and Assimilators was higher than those of Divergers and Accommodators in this experiment.

Thirdly, some previous studies reported a relation between gender and online learning patterns (Herring, 1992; Fahy, 2002), but none was found in this experiment. This finding might result from the fact that computers and Internet access were relatively inexpensive and had become readily available in recent years. Using computers and the Internet was no longer seen as an exclusively or even predominantly male activity. At the university this study was conducted, many of the study programs had a computer literacy requirement and a degree of familiarity with standard computer software packages was a basic requirement for both male and female students. Students were accustomed to online learning environment despite gender differences; thus no significant difference was found between male and female students on online learning behaviors and learning outcomes.

Finally, this study found no significant effect of learning style on total observation time and total designing time. The environment of the experiment design might contribute to this result. The authors of this experiment found that the arrangement of "online observation" was rather artificial. The subjects who were asked to "observe" the onscreen operation of others with their own computers might find it unhelpful to learn animation design and became reluctant to carry out online observation. It was likely that, in a more natural learning environment, subjects would consult others personally and observe what they were doing beside them, and consequently significant effect of different learning styles might be found. The authors of this experiment also found that the specialty of the task might be the reason why no significant effect of learning style was found on total designing time. In order to achieve the animation effects, all subjects had to spend a lot of time (more than half of the total time) dealing with the software of Flash.

## Conclusion

There was a potential value in the results of the study for instructors of online courses. As was discussed earlier, students of Abstract Conceptualization might find that abundant electronic documents satisfied their online learning requirements, whereas students of Concrete Experience might find that communicative learning environments, such as the BBS, met their online learning demands. Based on these results, instructors using online courses should seriously consider the diverse learning styles when designing and developing online learning modules for different students. Many scholars had offered various suggestions, which included designing course modules to meet the requirements of observing, participation, thinking and summarizing learning circles to accommodate different learning styles (Simpson & Du, 2004) or offering students a learning environment that provided a variety of ways by which they could access course information (Ruokamo & Pohjolainen, 2000).

In addition, maximizing students' learning outcome through online learning was one goal of using online courses. In order to acquire better learning outcomes, instructors of online courses were inclined to encourage students to participate in online discussion activities. This study gained a different conclusion. As could be seen from this study, the influence of online reading played an important role in students' learning outcome, so providing a large number

of electronic documents and giving enough time to let students to absorb knowledge by online reading might also be effective methods to improve the quality of online courses.

## Future research

Data analysis of this experiment proved that students belonging to different learning style types tended to have different online learning behaviors. It also produced the following questionable issues: Should we design online learning modules to meet the students' need of different learning style types? The answers to the question might be arguable. For example, in Miller's (2005) study, he claimed that understanding the compatibility of CBI (Computer Based-Instruction) formats for different styles allowed us to create instructional systems that were effective for all types of students, and CBI designers should put effort into designing systems that met the needs of all styles of learning/thinking. However, Robothm (1995) argued that a truly proficient learner was someone who could switch between styles and take advantage of all educational offerings and was someone who directed their own education. He believed that course design should focus on teaching students to self-direct their learning and not force students into a specific learning style. Taking these two different views into consideration, instructors or moderators of online courses should provide a variety of learning modules for students and help them learn how to switch between learning styles in order to take advantage of these choices. It was undoubtedly a challenging task, and would be a key issue of future research in distance education.

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## References

- Brown, E., Cristea, A., Stewart, C., & Brailsford, T. (2005). Patterns in authoring of adaptive educational hypermedia: a taxonomy of learning styles. *Education Technology & Society*, 8 (3), 77-90.
- Davidson-shivers, V., Nowlin, B., & Lanouette, M. (2002). Do multimedia lesson structure and learning styles influence undergraduate writing performance? *College Student Journal*, 36 (1), 20-31.
- Fahy, P.J. (2005). Student learning style and asynchronous computer-mediated conferencing (CMC) interaction. *The American Journal of Distance Education*, 19 (1), 5-22.
- Fahy, P.J. (2002). Epistolary and expository interaction patterns in a computer conference transcript. *Journal of Distance Education*, 17 (1), 20-35.
- Henke, H. (2001). *Learning theory: applying Kolb's learning style inventory with computer based training*, retrieved October 15, 2007, from <http://www.chartula.com/learningtheory.pdf>.
- Herring, S.C. (1992). Gender and participation in computer-mediated linguistic discourse. *Paper presented at the Annual Meeting of the Linguistic Society of America*, January 9-12, 1992, Philadelphia, USA.
- Howard, W.G., Ellis, H.H., & Rasmussen, K. (2004). From the arcade to the classroom: capitalizing on students' sensory rich media preferences in disciplined-based learning. *College Student Journal*, 38 (3), 431-440.
- Huang, R.H. (2003). *The theories and Methods of Computer-Supported Cooperative Learning*, Beijing: People's Education Press.
- John, M.C, Pamela, A.M., & William, P.D. (1991). Factor analysis of the 1985 revision of Kolb's Learning Style Inventory. *Educational and Psychological Measurement*, 51 (2), 455-462.

- Kayes, D.C. (2005). Internal validity and reliability of Kolb's Learning Style Inventory version 3 (1999). *Journal of Business and Psychology*, 20 (2), 249-257.
- Kolb, D.A. (1985). *Learning-style inventory: Self-scoring inventory and interpretation booklet*, Boston: McBer and Company.
- Liegle, J.O., & Janicki, T.N. (2006). The effect of learning styles on the navigation needs of web-based learners. *Computers in Human Behavior*, 22 (5), 885-898.
- Melara, G.E. (1996). Investigating learning styles on different hypertext environments: hierarchical-like and network-like structures. *Journal of Research on Computing in Education*, 14 (4), 313-328.
- Miller, L.M. (2005). Using learning styles to evaluate computer-based instruction. *Computers in Human Behavior*, 21 (2), 287-306.
- Oughton, J.M., & Reed, W.M. (2000). The effect of hypermedia knowledge and learning style on student-centered concept maps about hypermedia. *Journal of Research on Computing in Education*, 32 (3), 366-384.
- Raschick, M., Maypole, D., & Day, P. (1998). Improving field Instruction through Kolb learning theory. *Journal of Social Work Education*, 34 (1), 31-42.
- Reed, W.M., Oughton, J.M., Ayersman, D.J., Ervin, J.R., & Giessler, S.F. (2000). Computer experience, learning style, and hypermedia navigation. *Computers in Human Behavior*, 16 (6), 609-628.
- Robotham, D. (1995). Self-Directed Learning: the Ultimate Learning Style? *Journal of European Industrial Training*, 19 (7), 3-7.
- Ruokamo, H., & Pohjolainen, S. (2000). Distance learning in a multimedia networks project: main results. *British Journal of Educational Technology*, 31 (2), 117-125.
- Simpson, C., & Du, Y. (2004). Effects of learning styles and class participation on students' enjoyment level in distributed learning environments. *Journal of Education for Library & Information Science*, 45 (2), 123-136.
- Smith, D. M., & Kolb, D. A. (1986). *Learning Style Inventory: User's guide*, Boston: McBer & Company.
- Terrell, S. (1995). Predicting success in computer-mediated coursework. *Paper presented at the 6<sup>th</sup> International Conference on Technology and Distance Education*, October, San Jose, Costa Rica.
- Terrell, S. (2002). The effect of learning style on doctoral course completion in a web-based learning environment. *Internet and Higher Education*, 5 (4), 345-352.
- Veres, J.G. (1991). Improving the reliability of Kolb's revised Learning Style Inventory. *Educational and Psychological Measurement*, 51 (1), 143-150.