Are Learning Styles Relevant To Virtual Reality?

Chwen Jen Chen
Universiti Malaysia Sarawak

Seong Chong Toh
Wan Mohd Fauzy Wan Ismail
University Science Malaysia

Abstract

This study aims to investigate the effects of a virtual reality (VR)-based learning environment on learners with different learning styles. The findings of the aptitude-by-treatment interaction study have shown that learners benefit most from the VR (guided exploration) mode, irrespective of their learning styles. This shows that the VR-based environment offers promise in accommodating individual differences in terms of learning style. In addition, the significant positive effect of the VR (guided exploration) mode—which provides additional navigational aids—over the VR (non-guided exploration) mode—which does not provide additional navigational aids—also implies the importance of providing VR-based learning environments with proper instructional design to achieve the desired educational outcomes. (Keywords: virtual reality, learning style, aptitude-by-treatment interaction, learning environment.)

Aptitude-by-treatment interaction (ATI) research investigates the effects of learner aptitudes and traits on learning outcomes from different forms of instruction (Berliner & Cahen, 1973; Cronbach & Snow, 1969). The major assumption of this kind of research is that it is possible and desirable to adapt the nature of instruction to accommodate individual differences in terms of ability, style, or preference to improve learning outcomes. Interactions occur between aptitudes and treatments when individual differences predict different outcomes from alternative forms of structural or presentational properties. Tobias (1981) has given a clear elaboration to help in understanding the concept of interaction, which is summarized below.

In Figure 1 (page 124), the x-axis represents any individual difference measure, while the y-axis represents instructional outcomes. The functions, also known as regression slopes, in the figure represent the results for two different instructional treatments, A and B. This figure indicates that learners with low scores on the aptitude measure also perform poorly on the instructional outcome measure under treatment A. However, learners with similar low scores on the individual difference measure do quite well on the outcome measure when they are given treatment B. The contrary result is observed for learners with high scores on the aptitude measure. The ATI interaction in Figure 1 is a disordinal interaction. This means that not only the regression slopes are different, but also they are intersected (Jonassen & Grabowski, 1993). Such disordinal interactions are useful for appropriately assigning learners to different instructional treatments or methods.

Another type of ATI interaction is called ordinal interaction, where one treatment produces equal or better results for all learners within the range of aptitude studied. Figure 2, for example, depicts an ordinal interaction. The two slopes are the same but they do not intersect. This implies that all the learners within the range of aptitude studied perform better under treatment B, and the learners with high scores on the aptitude measure perform better than the learners with low scores on the aptitude measure for both groups.

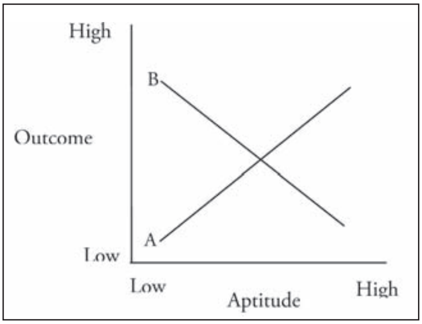

Figure 1. Disordinal interaction.

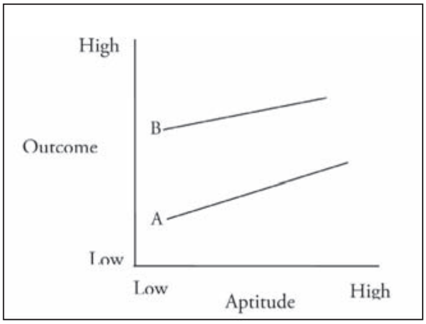

Figure 2. Ordinal interaction.

Indeed, research concerning individual differences in the context of VR is still in its infancy. Chen, Czerwinski, and Macredie (2000) reported an overview of some approaches and major findings of various research studies concerning the effects of individual differences on the use of this new technology. However, most of these studies focused particularly on the human-computer interaction aspect. Salzman, Dede, Loftin, and Chen (1999) have also pointed out the need for more study on the interaction of individual characteristics with the characteristics of VR. Looking at the scarcity of the ATI research, it is reasonable to investigate the effects of the VR-based learning environment of this project on learners with different aptitudes, focusing specifically on learning style. The following section elaborates how this aptitude was related to VR and explains why it was chosen specifically for the instruction of beginning drivers, which was the learning problem employed in this study.

LEARNING STYLE AND VR

Learning styles are general tendencies to prefer to process information in different ways (Jonassen & Grabowski, 1993). Kolb (1984) defines learning styles as one's preferred methods for perceiving and processing information. This definition evolves through his four-stage experiential learning cycle, as depicted in Figure 3. He further gives the working definition of experiential learning as the process whereby knowledge is created through the transformation of experience. Effective learners must be open to learning from new experiences, reflect upon what they observe in these experiences, integrate their conclusions into workable theories, and apply their theories in new situations.

According to Hunsaker and Alessandra (1986), the four-stage learning model indicates that the learner must constantly shift among abilities that are polar opposites of each other (concrete-abstract and active-passive). However, given the differences in individual abilities and preferences, and the demands of different occupations and situations, people develop different learning styles. Concrete experience, reflective observation, abstract conceptualization, and active experimentation are learning characteristics that represent the four stages of the learning cycle.

By plotting the perception of a person on the two primary learning-dimension continua, Kolb (1984) identified four types of learning styles: accommodator, assimilator, converger, and diverger. (See Figure 4.) Accommodators' dominant learning abilities are in the area of concrete experience and active experimentation. They are risk takers and rely on intuition and trial-and-error problem-solving methods. Accommodators are classified as doers and feelers. Assimilators, on the other hand, are best at abstract conceptualization and reflective observation. They are good at assimilating disparate observations into an integrated explanation. Assimilators are classified as watchers and thinkers.

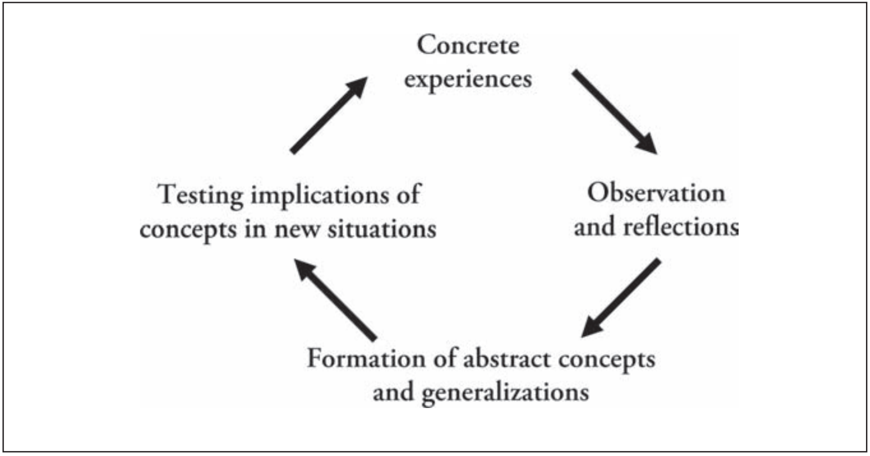

Figure 3. Kolb's experiential learning cycle (Adapted from Hunsaker & Alessandra, 1986).

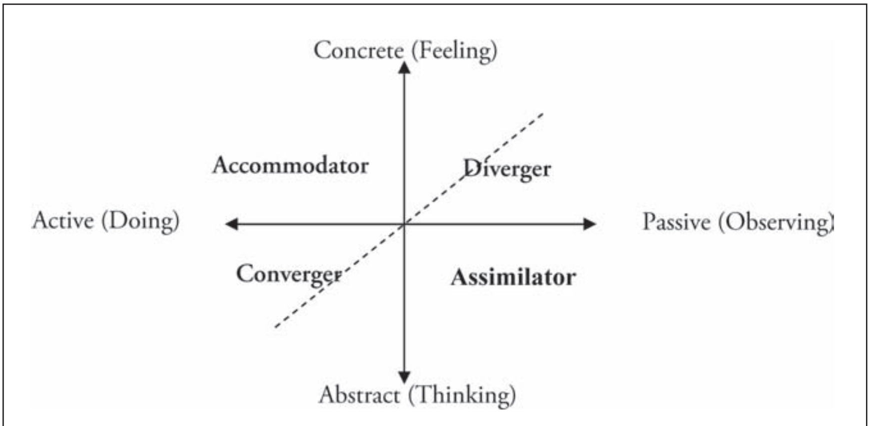

Figure 4. Learning style types (Adapted from Kolb, 1999).

Convergers grasp experience through abstract comprehension and transform through action, which means learning is best done through abstract conceptualization and active experimentation. They are good at solving specific problems with a single correct solution. Convergers are thinkers and doers. On the other hand, divergers learn best through concrete experience and reflective observation. They often have multiple perspectives of a situation and generate a multitude of divergent ideas. Divergers are feelers and watchers.

Chee (2001), Jensen, Seipel, Nejdl, and Olbrich (2002), and Ferreira and Müller (2005) are among others who have provided example applications of how VR can be designed to support Kolb's model of experiential learning. Indeed, according to Bell and Foyler (1997), experience—the main feature of VR—is of great benefit to all learning styles. In other words, VR could provide support to all four of Kolb's learning characteristics, namely concrete experience, reflective observation, abstract conceptualization, and active experimentation.

Chen, Toh, and Wan (2003) have conducted an initial study that looked into the limitations of the current instructional program for beginning car drivers in Malaysia, focusing solely on the cognitive aspect, and the potential of the VR technology to overcome those limitations. They found that the methods of instruction in the current instruction program for traffic rules and traffic signs of various road scenarios were well suited to accommodate learners who learn best through reflective observation and/or abstract conceptualization. On the other hand, virtual environments for such learning problems can be designed to accommodate all four of Kolb's learning characteristics. Hence, this project will further investigate the effects of the use of the VR-based learning environment, which was developed for this particular learning problem, on learners with different learning styles. Chen, Toh, and Wan (2004) provide a detailed description of the instructional design theoretical framework of this VR-based learning environment, and Chen and Toh (2005) provide an elaboration of the instructional development model that guided the design, development and evaluation process of the learning environment.

AIM OF THIS STUDY

This study aimed to obtain empirical data in the effort to gain insight into how three different learning modes (VR [guided exploration], VR [non-guided exploration], and Non VR) were related to the learners' learning styles.

Operational Definitions

VR (guided exploration): A learning mode that employs the developed VR-based learning environment. This learning environment provides additional navigational aids in the form of a tracer that provides a real-time indicator of the virtual vehicle position on a map, and directional arrows.

VR (non-guided exploration): A learning mode that employs the developed VR-based learning environment, except without the additional navigational aids.

Non VR: A conventional learning mode that relies on lectures and reading materials.

Assimilator learner: A learner in whom experience was grasped through abstract comprehension (conceptualizing) and transformed through thought (intention). This learning style combined abstract conceptualization and reflective observation (Kolb, 1999). The two combination scores (abstract conceptualization minus concrete experience, and reflective observation minus active experimentation) of this learner fell on the bottom right quadrant of the learning styles grid. Figure 4 shows a simplified version of the grid. A dashed diagonal line was introduced to equally separate the grid into two halves. Any diverger learner, whose learning style combined concrete experience and reflective observation or converger learner, whose learning style combined abstract conceptualization and active experimentation (Kolb, 1999) with the two combination scores that fell below the diagonal line was also classified as an assimilator learner. In other words, assimilator learners include learners who fulfilled Kolb's definition of assimilator, diverger learners with stronger Kolb's characteristic of reflective observation than concrete experience, and converger learners with stronger Kolb's characteristic of abstract conceptualization than active experimentation.

Accommodator learner: A learner in whom experience was grasped through feelings (apprehension) and transformed through action (extension). This learning style combined concrete experience and active experimentation (Kolb, 1999). The two combination scores of this learner fell on the top left quadrant of the learning styles grid shown in Figure 4. Any diverger learner or converger learner with the two combination scores that fell above the diagonal line was also classified as an accommodator learner. In other words, accommodator learners include those who fulfilled Kolb's definition of accommodator, diverger learners with a stronger Kolb's characteristic of concrete experience than reflective observation, and converger learners with a stronger Kolb's characteristic of active experimentation than abstract conceptualization.

RESEARCH DESIGN

A multiple-group pre-test-post-test quasi-experimental design (Spector, 1981) was employed in this study. This design involved two experimental groups (VR [guided exploration] and VR [non-guided exploration]) and a control group (Non VR). Each group was given a pre-test and a post-test. However, all these groups did not have pre-experimental sampling equivalence. The groups constituted intact classes, in which equivalency could not be presumed or assured.

The use of factorial design allowed the study of the interaction of the independent variable with one or more other variables, known as moderator variables (Fraenkel & Wallen, 1996). A 3 by 2 quasi-experimental factorial design was used in which the learning modes were crossed with the learning styles of the learners.

Variables

The independent variable was the learning mode (VR [guided exploration], VR [non-guided exploration], and Non VR). The dependent variable was the gain score, which was measured by the post-test score minus the pre-test score. The moderator variable, learning style (assimilator/accommodator) was included to investigate their effects on the three learning modes.

Population and Sample

Due to time and cost constraints, the accessible population for this study only encompassed the Form Four students (limited to those who had not undergone the driver instruction program) of any secondary schools that were well equipped with multimedia computer laboratories in the Penang Island. Form Four students were chosen because they were a non-examination class, and more important, they were within the targeted population as their age was approximately the minimum eligible age to undergo the beginning driver instruction program. School students, rather than individuals in the general public, were chosen to obtain better-controlled samples. The sample size was 184 and the average age of the participants was 16.45 years old.

Four different secondary schools were randomly selected (based on the simple random sampling technique) from the list of daily secondary schools in Penang Island. For each school, three intact classes were randomly chosen. All eligible students (those who had not undergone the driver instruction program) in the selected classes were included in the study, although all students who met the criterion were given the option of not participating. These selected classes were randomly assigned to either control or experimental groups.

Material and Instruments

The VR-based learning environment served as the treatment for the experimental groups. The instruments that were used include the VR-based test (pre-test and post-test) and Kolb Learning Style Inventory. These instruments are further described below.

VR-Based Test (Pre-test And Post-test)

The VR-based pre-test and VR-based post-test that were employed in this study were computer based. Each test consisted of 15 questions and aimed to assess the learners' understanding of traffic rules and traffic signs. Unlike the conventional theory test set by the Road Transport Department, which showed two-dimensional images, each of the questions in the VR-based test showed a three-dimensional simulation of a virtual road scenario and the learners were instructed to identify an observable error, if any. Both pre-test and post-test were similar in content but the order of the questions was different to avoid the set response effect.

Scoring

The total score of each test was 15. For each question, participants received a score of either 1 (correct answer) or 0 (incorrect answer), and a total score ranging from 0 to 15. This total score was multiplied by 100 to convert it to percentage.

Test Validity

Content validity of the VR-based test was determined by expert judgment (Gay & Airasian, 2003). Two subject matter experts from the Road Transport Department were requested to review the process used to develop the test as well as the test itself, and then made a judgment about how well these items represent the intended content area. Their comments were gathered and revisions were made on the test until they were satisfied with it through a recursive process.

Test Reliability

A small group evaluation or pilot study was carried out after the questions for the VR-based test were designed and validated. An item analysis was carried out on the results of the pilot study to obtain three types of information that were useful to improve the tests. These included the item difficulty index, item discrimination index, and pattern of responses to the various distracters. Reliability of the test was estimated using the Cronbach's alpha procedure.

Kolb Learning Style Inventory

The Kolb Learning Style Inventory (Version 3) was used to categorize the learning style of each participant into either assimilator or accommodator. Sewell (1986) has summarized the reliability statistics from a series of studies that are 0.54 to 0.83 using Spearman Brown, and alpha from 0.29 to 0.71. Test-retest reliabilities are 0.34 to 0.73.

A participant who took this test needed to complete 12 sentences that described learning. Each item had four endings and the participants were required to rank these endings according to how well he or she thought each ending described the way he or she learned. The scores indicated how much the participant relied on each of the four different learning characteristics: concrete experience, reflective observation, abstract conceptualization, and active experimentation. Then, combined scores (abstract conceptualization minus concrete experience, and reflective observation minus active experimentation) were calculated to determine the dominant type of learning style for each participant.

Procedures

Prior to the implementation of the study, permissions were obtained from a number of different parties for conducting the pilot study and the experimental study. Permissions were sought from the Penang State Education Department and the participating schools' principals, as well as from all participating students.

Small Group Evaluation (Pilot Study)

A group of Form Four students from a selected school served as the participants of this evaluation. These learners were not involved in the experimental study. After informing the learners on the purpose of this evaluation, they were given a training to familiarize themselves with the navigation of the virtual environments. Then, they were requested to explore the VR-based learning environment and to answer the post-test of the VR-based test. Item analysis was then conducted on the learners' answers to the post-test.

Experimental Study

Two weeks before the treatment, the learners were given the Kolb Learning Style Inventory and the VR-based pre-test. Then, just before the treatment, the experimental groups were given training on the navigation of the virtual environment. Immediately after the treatment, which took an hour, the learners were given the VR-based post-test.

RESULTS

Small Group Evaluation (Pilot Study)

The evaluation involved 30 Form Four students. Sixteen students were randomly selected from a Science stream class while the others were randomly selected from an Arts stream class to obtain greater variability. The post-test scores ranged from the lowest, 13.3%, to the highest, 100%. Based on guidelines by Hopkins (1998), question 1 and question 5 were classified as having good discrimination or good ability to measure individual differences while all the other questions provided excellent discrimination. The difficulty indices ranged from 0.3750 to 0.7500, which indicated that all the questions were of moderate difficulty. The Cronbach's alpha reliability coefficient was 0.83, which depicted the test questions as satisfactorily reliable. In addition, the responses to each question were well distributed.

Experimental Study

Distribution of Learners

The 184 learners were divided into three groups. Each group was assigned to one of the three learning modes. Table 1 shows the number of learners assigned to each learning mode.

Table 1: Learners' Distribution Across the Learning Modes

Learning mode	Number of learners
Non VR	64
VR (guided exploration)	62
VR (non-guided exploration)	58
Total	184

Testing of Hypotheses

ANCOVA was used to analyze the data. In this analysis, the pre-test scores served as the covariate. However, before ANCOVA was conducted, a series of tests to check the assumptions for this type of analysis were performed and this type of analysis was found to be appropriate for employment.

Testing of H_{01}

H_{01}: There is no significant difference in the gain score for the VR-based test between assimilator learners of each learning mode (VR [guided exploration], VR [non-guided exploration], and Non VR).

One-Way ANCOVA

A one-way analysis of covariance was conducted to examine if there was significant difference in adjusted mean of the dependent variable (gain score, which was measured by the post-test score minus the pre-test score) between the assimilator learners of each of the three learning modes, while controlling the pre-test. After adjusting for the pre-test scores, there was a significant difference between the assimilator learners of the three learning modes on the gain scores, $F(2, 96) = 19.017$, $p = 0.000$. (See Table 2.) This means that the learning mode had a main effect on the assimilator learners' gain scores. The effect size,

Table 2: One-Way ANCOVA of Gain Score by Learning Mode with Pre-Test Score as Covariate for Assimilator Learners

Dependent variable: Gain score

Source	Type III *SS*	*df*	*MS*	*F*	*Sig.*	η^2
Covariate						
Pre-test score	9030.899	1	9030.899	46.246	0.000	0.325
Main effect						
Learning mode	7427.500	2	3713.750	19.017	0.000	0.284
Error	18747.037	96	195.282			
Total	73955.556	100				

$p < 0.05$

calculated using η^2, was 0.284, which in Cohen's (1988) terms would be considered a large effect size. This effect size indicated that the learning mode effect accounted for 28.4% of the variance of the assimilator learners' gain scores.

The assimilator learners of the VR (guided exploration) mode had the largest adjusted mean (adjusted $M = 31.727$), the assimilator learners of the Non VR mode had a smaller adjusted mean (adjusted $M = 14.807$), and the assimilator learners of the VR (non-guided exploration) mode had the smallest adjusted mean (adjusted $M = 12.455$).

Pairwise Comparisons for One-Way ANCOVA

As the one-way ANCOVA yielded statistically significant results, follow-up post-hoc pairwise comparisons were conducted to evaluate pairwise differences among the adjusted means, as presented in Table 3 (page 132). The Holm's sequential Bonferroni procedure was used to control for Type I error across the three pairwise comparisons. Two comparisons were found significant: the comparison between the assimilator learners of the VR (guided exploration) mode and the assimilator learners of the VR (non-guided exploration) mode (p of 0.000 is less than 0.0167), and the comparison between the assimilator learners of the VR (guided exploration) mode and the assimilator learners of the Non VR mode (p of 0.000 is less than 0.025). The comparison between the assimilator learners of the Non VR mode and the assimilator learners of the VR (non-guided exploration) mode was not significant (p of 0.503 is not less than 0.05).

Summary of Testing H_{01}

The statistical results rejected the null hypothesis, H_{01}. The assimilator learners exposed to the VR (guided exploration) mode obtained a significantly higher gain score for the VR-based test than the assimilator learners exposed to the VR (non-guided exploration). The assimilator learners exposed to the VR (guided exploration) mode had also obtained a significantly higher gain score for the VR-based test than assimilator learners exposed to the Non VR mode. However, there was no significant difference in the gain score between the assimilator learners exposed to the VR (non-guided exploration) mode and the assimilator learners exposed to the Non VR mode.

Table 3: Summary of Post-Hoc Pairwise Comparisons between Assimilator Learners Across the Three Learning Modes

	Dependent variable (gain score)	
Comparison groups	Adj. mean difference	*Sig.*
VR (guided exploration) vs. VR (non-guided exploration)	19.272	0.000
VR (guided exploration) vs. Non VR	16.920	0.000
Non VR vs. VR (non-guided exploration)	2.352	0.503

Note: *The adjusted mean difference shown in this table is the subtraction of the second learning mode (on the lower line) from the first learning mode (on the upper line); for example, 19.272 (adjusted mean difference) = adjusted mean of VR (guided exploration) mode – adjusted mean of VR (non-guided exploration) mode.*

Testing of H_{02}

H_{02}: There is no significant difference in the gain score for the VR-based test between accommodator learners of each learning mode (VR [guided exploration], VR [non-guided exploration], and Non VR).

One-Way ANCOVA

A one-way analysis of covariance was conducted. After adjusting for the pre-test scores, there was a significant difference between the accommodator learners of the three learning modes on the gain scores, $F(2, 80) = 6.211$, $p = 0.003$. (See Table 4.) This means that the learning mode had a main effect on the accommodator learners' gain scores. The effect size, calculated using η^2, was 0.134, which in Cohen's (1988) terms would be considered a medium effect size.

Table 4: One-Way ANCOVA of Gain Score by Learning Mode with Pre-Test Score as Covariate for Accommodator Learners

Dependent variable: Gain score

Source	Type III *SS*	*df*	*MS*	*F*	*Sig.*	η^2
Covariate						
Pre-test score	6673.456	1	6673.456	36.557	0.000	0.314
Main effect						
Learning mode	**2267.515**	**2**	**1133.757**	**6.211**	**0.003**	**0.134**
Error	14603.910	80	182.549			
Total	49911.111	84				

$p < 0.05$

The accommodator learners of the VR (guided exploration) mode had the largest adjusted mean (adjusted $M = 24.749$), the accommodator learners of the VR (non-guided exploration) mode had a smaller adjusted mean (adjusted $M = 14.813$), and the accommodator learners of the Non VR mode had the smallest adjusted mean (adjusted $M = 12.616$).

Pairwise Comparisons for One-Way ANCOVA

As the one-way ANCOVA yielded statistically significant results, follow-up post-hoc pairwise comparisons were conducted to evaluate pairwise differences among the adjusted means, as presented in Table 5. The Holm's sequential Bonferroni procedure was used to control for Type I error across the three pairwise comparisons. Two comparisons were found significant: the comparison between the accommodator learners of the VR (guided exploration) mode and the accommodator learners of the VR (non-guided exploration) mode (p of 0.009 is less than 0.0167), and the comparison between the accommodator learners of the VR (guided exploration) mode and the accommodator learners of the Non VR mode (p of 0.001 is less than 0.025). The comparison between the accommodator learners of the Non VR mode and the accommodator learners of the VR (non-guided exploration) mode was not significant (p of 0.542 is not less than 0.05).

Table 5: Summary of Post-Hoc Pairwise Comparisons Between Accommodator Learners across the Three Learning Modes

	Dependent variable (gain score)	
Comparison groups	Adj. mean difference	*Sig.*
VR (guided exploration) vs. VR (non-guided exploration)	9.936	0.009
VR (guided exploration) vs. Non VR	12.133	0.001
VR (non-guided exploration) vs. Non VR	2.197	0.542

Note: *The adjusted mean difference shown in this table is the subtraction of the second learning mode (on the lower line) from the first learning mode (on the upper line); for example, 9.936 (adjusted mean difference) = adjusted mean of VR (guided exploration) mode – adjusted mean of VR (non-guided exploration) mode.*

Summary of Testing H_{02}

The statistical results rejected the null hypothesis, H_{02}. The accommodator learners exposed to the VR (guided exploration) mode obtained a significantly higher gain score for the VR-based test than the accommodator learners exposed to the VR (non-guided exploration). The accommodator learners exposed to the VR (guided exploration) mode also obtained a significantly higher gain score for the VR-based test than accommodator learners exposed to the Non VR mode. However, there was no significant difference in the gain score between the accommodator learners exposed to the VR (non-guided exploration) mode and the accommodator learners exposed to the Non VR mode.

Testing of H_{03}

H_{03}: In the VR (guided exploration) mode, there is no significant difference in gain score for the VR-based test between the assimilator learners and the accommodator learners.

One-Way ANCOVA

A one-way ANCOVA analysis of covariance was conducted to examine if there was significant difference in adjusted mean of the dependent variable (gain score) between assimilator learners and accommodator learners, while controlling the pre-test. After adjusting for the pre-test scores, it was found that there was no significant difference between the assimilator learners and the accommodator learners on the gain scores, $F(1, 59) = 0.165$, $p = 0.165$. (See Table 6.)

Table 6: ANCOVA of Gain Gcore by Learning Style with Pre-Test Score As Covariate for the VR (Guided Exploration) Mode

Dependent variable: Gain score

Source	Type III SS	df	MS	F	Sig.	η^2
Covariate						
Pre-test score	6309.712	1	6309.712	25.327	0.000	0.300
Main effect						
Learning style	**492.415**	**1**	**492.415**	**1.977**	**0.165**	**0.032**
Error	14698.541	59	249.128			
Total	72311.111	62				

p < 0.05

The adjusted mean for the assimilator learners was 31.198 and the adjusted mean for the accommodator learners was 25.484. The adjusted mean difference of 5.714 was not significant.

Summary of Testing H_{03}

The statistical results confirmed the null hypothesis, H_{03}. Although the adjusted mean of the assimilator learners of the VR (guided exploration) mode was higher than the accommodator learners of the same mode, this difference was not significant.

Testing of H_{04}

H_{04}: There is no interaction effect between the learners' learning styles and the learning modes (VR [guided exploration], VR [non-guided exploration], and Non VR) related to gain score of the VR-based test.

Two-Way ANCOVA

A 3 by 2 two-way ANCOVA was conducted to examine the effects of the learning modes on the performance in the VR-based test for assimilator learners and accommodator learners. The two-way ANCOVA results, as shown in Table 7 (page 136), indicated that the interaction between learning modes and learning styles was not significant, $F(2, 177)=1.762$, $p < 0.175$. This means the differences in the adjusted means of the gain score among the three learning modes did not vary as a function of learners' learning styles. Although the effect of the learning modes on the gain scores of the VR-based test did not depend on the learning style type, there were differences in gain scores among the learning modes for learners of different learning styles. The VR (guided exploration) mode had higher gain score than both the other two learning modes for both the assimilator and accommodator learners. In fact, the earlier statistical analyses for H_{01} and H_{02} revealed that these differences were significant.

The results in Table 7 also showed that the main effect due to learning style was not significant, $F(1, 177)=0.154$, $p < 0.695$. The adjusted mean of the gain scores for the assimilator learners, averaged across the three learning modes, 18.990, was slightly higher than the adjusted mean of the gain scores for the accommodator, 18.187.

Table 7: Two-Way ANCOVA of Gain Score by Learning Mode and Learning Style with Pre-test Score as Covariate

Dependent variable: Gain score

Source	Type III *SS*	*df*	*MS*	*F*	*Sig.*	η^2
Covariate						
Pre-test score	15558.709	1	15558.709	82.214	0.000	0.317
Main effects						
Learning mode (LM)	8316.168	2	4158.084	21.972	0.000	0.199
Learning style (LS)	29.223	1	29.223	0.154	0.695	0.001
2-way interaction						
LM LS	**666.818**	**2**	**333.409**	**1.762**	**0.175**	**0.020**
Error	33496.593	177	189.246			
Total	123866.667	184				

$p < 0.05$

Table 8 presents the means, standard deviations, adjusted means, and standard error of the gain score by the learning mode and the learning style, and Figure 5 (page 136) illustrates the interaction effect between the three learning modes and the learners' learning styles (assimilator and accommodator) on gain score.

Table 8: Means, Standard Deviations, Adjusted Means, and Standard Errors of Gain Score by Learning Mode and Learning Style

		Gain score			
Learning mode	Learning style	*M*	*SD*	Adjusted *M*	*SE*
VR (guided	Assimilator (N=35)	30.2857	18.1023	30.923[a]	2.326
exploration)	Accommodator (N=27)	26.6667	19.4804	25.352[a]	2.651
VE(non-guided	Assimilator (N=31)	11.6129	18.7749	11.706[a]	2.471
exploration)	Accommodator (N=27)	14.5679	10.1336	15.638[a]	2.650
Non VR	Assimilator (N=34)	17.0588	13.5529	14.342[a]	2.378
	Accommodator (N=30)	11.1111	17.3610	13.570[a]	2.526

Note: [a] *Evaluated at covariate appeared in the model: pre-test = 58.1160*

Summary of Testing H_{04}

The statistical results confirmed the null hypothesis, H_{04}. There was no significant interaction between the three learning modes and the learners' learning styles, which means the effect of the learning modes on the gain scores of the VR-based test did not depend on the types of learning style. The main effect due to learning style was not significant.

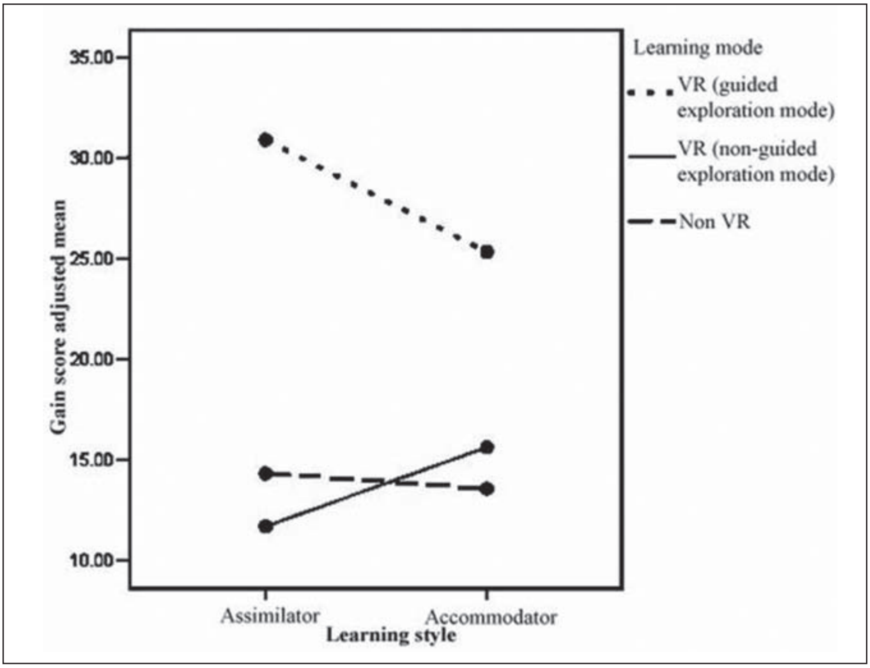

Figure 5. Plot of interaction between learning mode and learning style.

DISCUSSION

Effects of the Learning Mode on Learning Based on Learning Style Types

Kolb (1984), Fielding (1994), Gardner (1985), Slavin (2000), and Woolfolk (1998) are a few of those researchers who agreed that individuals learn better when subject matter is presented in a way consistent with their preferred learning style. The finding of this study supports this view. Kolb (1984) identified four learning characteristics: abstract conceptualization and concrete experience on the extreme ends of the continuum that represents how one prefers to perceive the environment, and reflective observation and active experimentation as the extreme ends on another continuum that represents how one prefers to process incoming information. The Non VR mode that relies on lecture and reading material is more suited for candidates with learning styles prone to the left end of both continuums. This explains the finding that the assimilator learners performed better than the accommodator learners in this mode. Conversely, in the VR (non-guided exploration) mode, the accommodator learners outperformed the assimilator learners. The lack of navigational aids also implies the necessity to actively explore virtual environments in order to solve the learning problem posed. Hence, learners with Kolb's characteristics of active experimentation benefit more from this learning mode.

Learners exposed to the VR (guided exploration) mode significantly outperformed the learners exposed to the VR (non-guided exploration) mode. This result can be explained by the limited-capacity assumption of Mayer's (2002) cognitive theory of multimedia learning. Indeed, this assumption, which emphasizes the importance of not overloading the working memory during the learning process, is closely associated with the cognitive load theory (Sweller, 1999). The possible explanation to this finding, interpreted within this context, is elaborated below.

Exploring a virtual environment involves navigating within it. Generally, navigation is the process of determining a path to be traveled by any object through any environment (Darken & Sibert, 1993). However, users' navigation in virtual environments can be difficult (Darken & Cevik, 1999; Darken & Sibert, 1993; Marsh & Smith, 2001; Schwarz, 2001; Smith & Marsh, 2004; Stankiewicz, McCabe, Kelly, Tara, & Legge, 2003). One of the contributing factors is the problem of disorientation or getting lost (Marsh & Smith, 2001), which basically means the users of virtual environments have a problem in maintaining knowledge of their location and orientation while they move through the space (Darken & Sibert, 1993). This knowledge is related to a user's spatial orientation ability, and the schema for this ability differs among individuals.

The problem associated with navigation within virtual environments also implies that creating a VR-based learning environment that requires the learner to explore the virtual environments during the learning process by navigating within it will impose extraneous cognitive load. The efforts to stay oriented when navigating through virtual environments take up mental resources that will subsequently reduce the amount of mental resources available to understand the domain concepts or knowledge. A study by McConathy and Doyle (1993) supports this view, where they found that failure to establish viewer orientation in their interactive displays caused orientation to be the viewer's first cognitive task, before proceeding to the intended information processing task. As highlighted by Cooper (1998), when the intrinsic cognitive load is high (difficult domain concepts or knowledge) and the extraneous cognitive load is high, then total cognitive load will exceed mental resources and learning may fail to occur.

According to Cooper (1998), in order to reduce the total cognitive load to within the bounds of mental resources, the level of extraneous cognitive load must be modified by changing the instructional materials presented to learners. Marsh and Smith (2001) pointed out that the lack of navigation cues is a major cause of navigational difficulty within virtual environments. The use of maps, for example, has been found to improve navigation performance within virtual environments (Darken & Sibert, 1993, 1996; Darken & Cevik, 1999; Sayers, Wilson, & McNeill, 2004; Stankiewicz et al., 2003). Leutner (1993) in his study has also shown that providing additional information about the current status of system variables makes the system more transparent, subsequently reducing the level of difficulty of the problem.

The instructional design based on the cognitive load theory (Sweller, 2003) functions to provide the otherwise missing schema when dealing with novel information. In this regard, the significant positive effect of the VR (guided exploration) mode when compared with the VR (non-guided exploration) mode proves that the use of additional navigational aids (tracer and directional arrows) in the VR (guided exploration) mode provides support to any missing spatial orientation schema that is required to stay oriented while navigating within a virtual environment. With the availability of such support, the amount of mental resources that deal with extraneous cognitive load can be reduced, leaving more resources for intrinsic cognitive load (Cooper, 1998).

The VR (guided exploration) mode showed significant positive effects for both assimilator learners and accommodator learners. In fact, the effects of this learning mode on both assimilator learners and accommodator learners were almost equivalent, which also suggested that learning styles did not significantly influence the learners' performance on the VR-based test. A possible explanation of this finding is that in the VR (guided exploration) mode, the utilization of both virtual environments and conventional materials involved all elements of Kolb's model. Virtual environments that simulate mimic to real world road scenarios provide concrete experience that allows learners to actively explore through them and the conventional material, which is passively presented in the form of text and images, requires more of Kolb's characteristics of reflective observation and abstract conceptualization. As the learning mode covers all four extreme ends of the perception continuum and the information-processing continuum, it benefits both the assimilator learners and the accommodator learners. In other words, this learning mode supports Kolb's model of experiential learning by providing concrete experience, reflective observation, abstract conceptualization, and active experimentation.

Interaction Effect

The interaction effect between the learners' learning styles and the three learning modes was also not significant. In other words, the effects of the learning modes on learning did not depend on the learners' differences in terms of learning style. However, among the three learning modes, VR (guided exploration) mode provided the most positive effect to both assimilator learners and accommodator learners. Indeed, both assimilator learners and accommodator learners benefited equally from this learning mode. This implies that the learners benefit most from the VR (guided exploration) mode, irrespective of their learning styles.

CONCLUSION

The vast majority of the research into virtual environments for instructional use is technology-driven, rather than taking into account the human factor. There has been little research on how learner characteristics interact with the features of virtual environments either to aid or inhibit learning. The ATI study that has been conducted provides more understanding of this aspect. The findings of this study have shown that learners benefit most from the VR (guided exploration) mode, irrespective of their learning styles. This shows that the VR-based learning environment offers promise in accommodating individual differences in terms of learning style. In addition, the significant positive effect of the VR (guided exploration) mode over the VR (non-guided exploration) mode also implies the importance of providing VR-based learning environments with proper instructional design in order to achieve the desired learning outcomes.

Contributors

Chwen Jen Chen is a Cognitive Sciences and Human Development lecturer attached to Universiti Malaysia Sarawak and has been actively involved in the research and development work utilizing virtual reality technology since 1996. Parts of the work done in the project reported in this paper have been published in journals such as the *Journal of Interactive Learning Research*, *Educational Technology Research and Development*, and various proceedings. (Address: Chwen Jen Chen, Universiti Malaysia Sarawak, 94300 Kota Samarahan, Sarawak, Malaysia; cjchen@fcs.unimas.my.)

Seong Chong Toh and Wan Mohd Fauzy are associate professors in instructional technology. Both of them are currently attached to the Centre for Instructional Technology and Multimedia, University Science Malaysia. (Address: Seong Chong Toh and Wan Mohd Fauzy, University Science Malaysia, 11800 Minden, Penang, Malaysia; tohsc@usm.my, fauzy@usm.my.)

References

Bell, J. T., & Foyler, H. S. (1997). Ten steps to developing virtual reality applications for engineering education. Proceedings of *American Society for Engineering Education Annual Conference*. Milwaukee, WI. Available: http://www.cs.uic.edu/~jbell/Professional/Papers/aseepap5.pdf.

Berliner, D. C., & Cahen, L. S. (1973). Trait-treatment interaction and learning. In F. N. Kerlinger (Ed.), *Review of research in education,* Vol.1 (pp. 58–94). Itasca. IL: Peacock.

Chee, Y. S. (2001). Virtual reality in education: Rooting learning in experience. *Proceedings of the International Symposium on Virtual Education* (pp. 43–54). Busan, South Korea. Available: http://yamsanchee.myplace.nie.edu.sg/Publications/2001/ISVE2001Invited.pdf.

Chen, C., Czerwinski, M., & Macredie, R. (2000). Individual differences and virtual environments: Introduction and overview. *Journal of the American Society for Information Science*, *51*(6), 499–507.

Chen, C. J., & Toh, S. C. (2005). A feasible instructional development model for virtual reality (VR)-based learning environments: Its efficacy in the novice car driver instruction of Malaysia. *Educational Technology Research & Development*, *53*(1), 111–123.

Chen, C. J., Toh, S. C., & Wan, M. F. (2003). Virtual reality: a potential technology for providing novel perspective to novice driver education in Malaysia. In N. Ansari et al. (Eds.), *Proceedings of the International Conference on Information Technology: Research and Education* (pp. 184–188). New Jersey: IEEE.

Chen, C. J., Toh, S. C., & Wan, M. F. (2004). The theoretical framework for designing desktop virtual reality-based learning environments. *Journal of Interactive Learning Research*, *15*(2), 147–167.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences*. Hillsdale, NJ: Erlbaum.

Cooper, G. (1998). *Research into cognitive load theory and instructional design at UNSW*. Retrieved May 3, 2004 from http://education.arts.unsw.edu.au/CLT_NET_Aug.

Cronbach, L. J. & Snow, R. E. (1969). *Individual differences in learning ability as a function of instructional variables*. (Final report, Contract No. OEC-4-6-061269-1217), Stanford, CA: Stanford University, School of Education. (U.S. Office of Education, ERIC Document Reproduction Service No. ED 029 001).

Darken, R. P., & Cevik, H. (1999). Map usage in virtual environments: Orientation issues. *Proceedings of IEEE Virtual Reality 99* (pp. 133–140), Houston, TX. Available: http://www.movesinstitute.org/darken/publications/MapUsage.pdf.

Darken, R. P., & Sibert, J. L. (1993). A toolset for navigation in virtual environments. *Proceedings of ACM User Interface Software & Technology* (pp. 157–165), Atlanta, GA. Available: http://www.movesinstitute.org/darken/publications/toolset.pdf.

Darken, R. P., & Sibert, J. L. (1996). Wayfinding strategies and behaviors in large virtual worlds. *Proceedings of ACM SIGCHI 96* (pp. 142–149), Vancouver, BC. Available: http://www.movesinstitute.org/darken/publications/strategies.pdf.

Fielding, M. (1994). Valuing difference in teachers and learners: Building on Kolb's learning styles to develop a language of teaching and learning. *The Curriculum Journal*, *5*, 393–417.

Fraenkel, J. R., & Wallen, N. E. (1996). *How to Design and Evaluate Research in Education* (3rd ed.). USA: McGraw-Hill.

Ferreira, J. M., & Müller, D. (2005). Online labs and the MARVEL experience. *International Journal of Online Engineering*, *1*(1). Available: http://www.ijoe.org/ojs/viewarticle.php?id=4&layout=abstract.

Gardner, H. (1985). *Frames of mind: The theory of multiple intelligences*. New York: Basic Books.

Gay, L. R., & Airasian, P. (2003). *Educational research: Competencies for analysis and applications*. Upper Saddle River, NJ: Merrill Prentice Hall.

Hopkins, K. D. (1998). *Educational and psychological measurement and evaluation* (8th ed.). Boston: Allyn and Bacon.

Hunsaker, P. L., & Alessandra, A. J. (1986). *The art of managing people*. New York: Touchstone.

Jensen, N., Seipel, S., Nejdl, W., & Olbrich, S. (2002). *COVASE: Collaborative Visualization for Constructivist Learning*. (Technical Report VASE 3 Q4: 2002). Retrieved August 4, 2002, from http://www.kbs.uni-hannover.de/Arbeiten/Publikationen/2002/covase_trq402.pdf.

Jonassen, D. H., & Grabowski, B. L. (1993). *Handbook of individual differences, learning, and instruction*. New Jersey: Lawrence-Erlbaum Associates.

Kolb, D. A. (1984). *Experiential learning: Experience as a source of learning and development*. Englewood Cliffs, NJ: Prentice-Hall.

Kolb, D. A. (1999). *The Kolb Learning Style Inventory*. Boston: Hay Resources Direct.

Leutner, D. (1993). Guided discovery learning with computer-based simulation games: Effects of adaptive and non-adaptive instructional support. *Learning and Instruction*, *3*, 113–132.

Marsh, T., & Smith, S. P. (2001). Guiding user navigation in virtual environments using awareness of virtual off-screen space. In V. Paelke & S. Volbracht (Eds.), *Proceedings of the Workshop on Guiding Users through Interactive Experiences—Usability Centred Design and Evaluation of Virtual 3D Environments* (pp. 149–154). Aachen, Germany: Shaker Verlag.

Mayer, R. E. (2002). *Multimedia Learning*. Cambridge: Cambridge University Press.

McConathy, B. J., & Doyle, M. (1993). Interactive displays in medical art. In R. Ellis, M. Kaiser, & A. J. Grunwald (Eds.), *Pictorial Communication in Virtual and Real Environments*, 2nd ed. (pp. 97–110). London: Taylor & Francis.

Salzman, M. C., Dede, C., Loftin, R. B., & Chen, J. (1999). A model for understanding how virtual reality aids complex conceptual learning. *Presence: Teleoperators and Virtual Environments*, *8*(3), 293–316. Cambridge, MA: Massachusetts Institute of Technology.

Sayers, H. M., Wilson, S., & McNeill, M. D. (2004). Navigational tools for desktop virtual environment interfaces. *Virtual Reality*, *7*(3/4), 131.

Schwarz, J. (2001). Lost in virtual space: Gender differences are magnified. Retrieved May, 22, 2004 from http://www.uwnews.org/article.asp?articleID=2410

Sewell, T. J. (1986). *The measurement of learning style: A critique of four assessment tools.* [Research report]. Green Bay: Wisconsin University Assessment Center. (ERIC Document Reproduction Service No. ED 267 247).

Slavin, R. E. (2000). *Educational psychology: Theory and practice*. Boston: Allyn & Bacon.

Smith, S. P., & Marsh, T. (2004). Evaluating design guidelines for reducing user disorientation in a desktop virtual environment. *Virtual Reality*, *8*(1), 55–62.

Spector, P. E. (1981). *Research designs*. Newbury Park, CA: Sage.

Stankiewicz, B. J., McCabe, M., Kelly, T., & Legge, G. E. (2003). Lost in virtual space: Estimating state uncertainty. *Journal of Vision*, *3*(9). Available: http://journalofvision.org/3/9/14/.

Sweller, J. (1999). *Instructional design in technical areas*. Camberwell, Australia: ACER.

Sweller, J. (2003). Evolution of human cognitive architecture and instructional design. *The 4th International Conference on Cognitive Science*, The University of New South Wales: Sydney.

Tobias, S. (1981). Adapting instruction to individual differences among students. *Educational Psychologist, 16*, 111–120.

Woolfolk, A. (1998). *Educational psychology*. Boston: Allyn & Bacon.