Behavioral Intention of Using Virtual Reality in Learning

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ABSTRACT

This study integrated the unified theory of acceptance and use of technology (UTAUT) and the four stages of Kolb's learning style—concrete experience, reflective observation, abstract conception, and active experimentation—to investigate the factors affecting students' behavioral intention to use a virtual reality headset (VRH) in learning. The research model, constructed using structural equation modeling, included the four constructs of the UTAUT, namely performance expectancy, effort expectancy, social influence, and facilitating condition. Hypotheses on whether the four stages of Kolb's learning style and the four constructs of the UTAUT significantly affect behavioral intention to use VRHs in learning were proposed and tested through inference analysis. The results show that only the concrete experience stage of Kolb's learning style has a positive and significant effect on users' behavioral intention to use VRHs in learning, whereas all four constructs of the UTAUT do. These findings should be applied by educational institutions to increase VRH use in learning.

Keywords

Virtual Reality; Technology Acceptance; Learning Style; Behavioral Intention

1. INTRODUCTION

Virtual reality (VR) is the use of three-dimensional (3D) graphics systems in combination with various interference devices to realize the effect of immersion in an interactive virtual environment. Different technologies and trends have influenced the development of VR. VR headsets (VRHs), which are head-mounted displays that provide a vivid user experience, are a major technology. In the field of education, the immersive experience that VR provides can be used by trainers to improve learners' intention of engaging in learning activities [1]. Specifically, VR can be applied in the learning of various subjects, such as physics, chemistry, demographics, and linguistics [2-7]. The intrinsic

properties and cognitive mechanism of VR technologies enable learners to consciously focus on what they are experiencing and to engage in more meaningful learning [8]. Bell et al. stated that VR has the potential to be a powerful tool in engineering education, one that brings experience-based learning to all students by addressing the needs of students with alternative learning styles, and enhancing the impact of educational presentations [9]. In a VR environment, the human mind can perceive nonexistent objects in a creative sense. VRHs are becoming increasingly adopted in education. Understanding how students perceive VRH technology would therefore help improve VRH user experience.

Studies on the acceptance of information technology (IT) have employed various methodologies. Some studies have focused on determinates such as behavioral intention and usage behavior [10, 11], whereas others have approached it from the perspective of the organization [12] or fitness of task [13, 14]. Many recent studies have suggested that differences between individuals influence IT acceptance and use [15]. However, studies on the relationship between individual learning style and technology acceptance have yielded inconsistent results. Differences in individuals' learning styles can explain the learning variations between individuals in an instructional process. Some studies have recommended comprehensive research on the relationships between learning styles and virtual environments [16]. To the best of the present authors' knowledge, no studies have yet investigated the behavioral intention of VRH use in learning, which is an emergent trend and technology. Therefore, in this study, the research fundamentals of IT acceptance and learning style are utilized to comprehensively study the following: 1. students' behavioral intention to use VRHs for learning; 2. the effect of the four stages of learning style on students' behavioral intention; and 3. the effect of IT acceptance on students' behavioral intention on the basis of the unified theory of acceptance and use of technology (UTAUT).

2. LITERATURE REVIEW

In a 3D VR environment, users can use human senses to manipulate or interact with virtual objects and circumstances [17-19]. The prominent advantage of 3D VR is its ability to realize real-time interactions, which distracts users from the real enviroment as they are immersed into a 3D environment. Pan et al. explained the operational mechanism of a 3D VR system that supports interactions between users and the system as follows: the users' body gestures are instantaneously registered as input

signals in the system, on the basis of which the system performs a reciprocal action [18]. Jonassen, Burdea, and Coiffet posited that 3D simulation environments enhance users' cognition of nonexistent objects by transforming difficult abstract concepts into concrete visualizations [8, 20]. Because of the superior interactivity of 3D VR, which captivates users and fully engages them in the VR environment, educators are beginning to apply VR technology to teaching and learning activities [1].

The ability of technology to simulate real-life situations in 3D graphics environments is highly beneficial to learners. The use of 3D VR systems in education is considered the most suitable alternative to traditional text- and web-based systems [7, 16]. For example, Shih and Yang designed a virtual 3D English classroom in which users could verbally interact with the virtual objects in real-time [7]. This VR design improved the interaction, typing, reading, and listening comprehension of students and augmented the learning autonomy of English as a Foreign Language undergraduate students. Virvou and Katsionis examined whether the high sophistication of VR educational game design increases the likability of players [21]. Hodgson et al. used a portable VR kit as a research tool to simulate a full-scale grocery store; the participants navigated through the virtual store on a realistic spacious grassy field [22]; the veridical navigational interface of the simulation confirmed the viability of using realistic sites for VR experiments. Another controlled VR experiment was conducted by Antonieta, who used a full HMD-based VR environment on freshmen of the design department at Ball State University and reported that the swift real-time feedback of VR immersive environments may enhance students' understanding of architectural spatial design [23]. Freina and Ott argued that the immersive experience of VR distracted from the sense of being in a task environment by reducing the users' awareness of time and real-life occurrences and by forcing the perception that the users are physically present in a nonphysical world [24]. Furthermore, the application of VR in education provides a safe training platform as it avoids the physical dangers of real-life training situations while widening the range of learning and increasing the learners' engagement and motivation.

Experiential learning refers to learning styles and approaches that are adopted to improve learning effectiveness. Kolb proposed that individuals develop their own learning styles during the learning process [25]. Keefe claimed that the learning style, which is characterized by cognitive, affective, and psychological processes, would determine how learners perceptually process and absorb learning materials [26]. Gregorc asserted that the differences in the learning styles of individuals indicated their differential priority of specific learning strategies in certain circumstances [27]. Bandura indicated that rather than use approaches that were beyond their capabilities, individuals tend to adopt a learning strategy that helps them achieve the learning goals within the constraints of their capabilities [28]. Subsequently, Bandura added that because self-efficacy in education derives from personal experience, the learning strategies for self-efficacy varies between students depending on their exposure to information [29]. As other scholars have noted, experimental education, which emphasizes direct feedback and active interaction, enhances the learning experience [30, 31]. Pashler et al. reported that the aggregation of a multitude of personal learning experiences has resulted in the development of various models of learning styles [32], and Wolff and Manolis et al. have advocated the Kolb's learning style model, emphasizing the vast empirical evidence for the effectiveness of the model and its wide acceptance in academia and in practice [33, 34].

Experimental learning transforms the aggregation of experience into knowledge and identifies four types of learners: diverger, assimilator, converger, and accommodator [25]. Kolb introduced three crucial models for experimental learning, namely Dewey's model of learning, Lewin's model of action research and laboratory training, and Piaget's model of learning and cognitive development [35]. Kolb and Kolb concluded that experimental education improves students' meta-thinking ability and facilitates self-directed learning [36]. Meanwhile, Terrell observed that most of the Computing Technology in Education doctoral students adopted their own experiences and strategies to succeed in a course implemented in a web-based environment [37]. Using Kolb's learning style inventory (LSI), Wang et al. investigated the influence of formative assessment and learning style on students' learning achievement in a web-based learning environment and found that students characterized as divergers provided the best performance, followed by assimilators, accommodators, and convergers [38]. Sun et al. reported that students adopting the accommodator learning style made the highest achievements and that those engaging in an online virtual laboratory obtained higher grades than did those learning in a traditional class setting; they also reported that students preferred the online virtual learning experience over textbook learning [39]. Shaw reported that the learning scores of students who were classified on the basis of Kolb's LSI exhibited heterogeneity, with accommodators demonstrating the best learning performance [19]. Sahasrabudhe and Kanungo found that the effectiveness of media choice on a e-learning program was regulated by the learners' learning styles and the learning domain of the program [40].

The adoption of computers and IT has substantially increased the productivity of firms, but only when they are accepted and used by employees [41]. Numerous theoretical models that explore information system, psychology, and sociology have been proposed [11, 42, 43]. For example, Venkatesh et al. introduced the UTAUT, which clarifies the dynamics and motivation for users to engage with new technologies [44]. Subsequently, Carlsson et al. successfully employed the UTAUT to explain users' acceptance of mobile devices and services [45], while Wu et al. applied the UTAUT to examine the behavior of mobile-phone users toward 3G service; they reported that UTAUT's constructs, specifically performance expectancy, social influences, and facilitating conditions, significantly influenced the behavioral intention of users [46]. Also using the UTAUT, Marchewka and Kostiwa explored students' frequent use of a web-based course management software in higher education [47], and Chiu and Wang examined learners' continuance intention in web-based learning, finding that performance expectancy, effort expectancy, and computer self-efficacy influence learners' continued use of web-based learning [48]. From the interactional psychology perspective and by using the five-factor model of the UTAUT, Barnett et al. explored how and why individuals use technology and empirically confirmed that performance expectancy, effort expectancy, and social influence affect technology use [49]. They argued that expectation, conscientiousness, and neuroticism are linked to perceived and actual use of technology. Teo and Noyes stated that the UTAUT can be used to interpret preservice teachers' intention of IT use and acceptance [50].

3. METHODOLOGY

The UTAUT, incorporated with Kolb's learning style, was adopted in this study to examine the differential effects of using VRHs on the behavioral intention of learning. Eight hypotheses were proposed, and an online questionnaire was designed to

survey the user experience of university students. The collected results were analyzed through structural equation modeling (SEM) to verify our hypotheses.

3.1 Hypotheses

Studies on information systems have examined how and why individuals adopt new information technologies. This broad area of inquiry comprises several smaller research domains, one of which focuses on the individual acceptance of technology by using intention or usage as a dependent variable [10, 11]. Other domains have focused on implementation success at the organizational level [12] and on task–technology fit [13, 14]. Each of these streams makes important and unique contributions to the literature on user acceptance of IT.

The UTAUT integrates eight specific models of the determinants of intention and usage of IT and states that four constructs— performance expectancy, effort expectancy, social influence, and facilitating conditions—play significant roles as the direct determinants of user acceptance and usage behavior [44]. The UTAUT was employed in our study for the following reasons: First, it was formulated based on conceptual and empirical similarities across the eight models. Second, these models were empirically compared using within-subject longitudinal data from four organizations. Third, it was empirically tested using original data from the four organizations and then cross-validated using new data from two other organizations. These tests have provided strong empirical support for the UTAUT, which is considered the most prominent and unified model in the domain of IT adoption research [51].

In addition, Kolb's LSI, one of the most influential and widely applied instruments used to measure individual learning preference, was used in this study [19, 37]. Kolb's learning styles have gained widespread acceptance and have provided a foundation for understanding experiential learning [34].

Understanding the adoption and use of IT is crucial in the field of information systems. Several conceptual models have therefore been proposed to explain how and why individuals use technology [49, 52-55]. DiTiberio reported that extroverted learners prefer collaborative learning, whereas introverted learners are more likely to be comfortable with computer-assisted instruction [56]. Similarly, Komarraju examined the relationship between personality traits and Kolb's learning styles [57], and Kim studied the effects of personality traits [58] and Kolb's learning styles on academic achievements in a blended learning environment. In this study, we mainly focused on behavioral intention from the perspective of learning. Therefore, we propose four hypotheses related to concrete experience, reflective observation, abstract conception, and active experimentation that correspond to the four stages of Kolb's learning styles:

H1: Concrete experience has a significant effect on the behavioral intention to learn when VRHs are used.

H2: Reflective observation has a significant effect on the behavioral intention to learn when VRHs are used.

H3: Abstract conception has a significant effect on the behavioral intention to learn when VRHs are used.

H4: Active experimentation has a significant effect on the behavioral intention to learn when VRHs are used.

In addition, from the perspective of UTAUT, this study considers the constructs of performance expectancy, effort expectancy, and social influence. Performance expectancy is defined as the degree to which an individual believes that using the system would help him or her to improve job performance [44]; this relationship is likely moderated by gender and age. Many studies have shown that performance expectancy significantly affects individuals' behavioral intention [45, 47-50, 59]. Accordingly, we propose our fifth hypothesis:

H5: Performance expectancy has a significant effect on the behavioral intention to learn when VRHs are used.

Effort expectancy is defined as the degree of ease associated with the use of any system [44]. Prior research supports the idea that constructs related to effort expectancy are strong determinants of individuals' intention among women and older workers [43, 44]. In addition, many studies have shown that effort expectancy significantly affects individuals' behavioral intention [45, 47-50, 59-61]. Accordingly, we propose our sixth hypothesis:

H_6: Effort expectancy has a significant effect on the behavioral intention to learn when VRHs are used.

Social influence is defined as the degree to which an individual perceives that it is important that others believe he or she should use a new system [44]. Women tend to be more sensitive to others' opinions and therefore find social influence to be more salient when forming an intention to use new technology [43]. As in the case of performance and effort expectancies, gender effects may be driven by psychological phenomena embodied within socially constructed gender roles [62]. Several studies have shown that effort expectancy significantly affects individuals' behavioral intention [45, 47-50, 59-61]. Accordingly, we propose the seventh hypothesis:

H_7: Social influence has a significant effect on the behavioral intention to learn when VRHs are used.

Finally, facilitating conditions are defined as the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of a system [44]. Issues relating to the support infrastructure, a core concept within the facilitating conditions construct, are largely captured within the effort expectancy construct, which reflects the ease with which that tool can be applied [43]. Research has shown that facilitating conditions significantly affect individuals' behavioral intention [46, 63]. Thus, we propose our eighth hypothesis:

H_8: Facilitating conditions have a significant effect on the behavioral intention to learn when VRHs are used.

3.2 Measurement of Variables

All items in the questionnaire were evaluated on a Likert-type five-level scale: strongly disagree, disagree, neither agree nor disagree, agree, and strongly agree; these responses were scored 1, 2, 3, 4, and 5 points, respectively. Manolis suggested transforming Kobe's LSI from a categorical measure to a continuous measure [34]. Accordingly, a 48-item questionnaire from Kolb's LSI version 3.1 incorporated with the aforementioned scoring scale was employed in this study.

In addition, performance expectancy can be referred by [44]. In the present study, this definition was modified as the degree to which a student believes that using a VRH would help him or her to improve his or her academic performance. Four items regarding helpfulness, productivity, effectiveness, and academic performance were designed for performance expectation (Table 1).

Table 1. Items of performance expectation

Item
Learning by using a VRH is helpful for me.
Learning by using a VRH is more productive for me.
Learning by using a VRH will improve my effectiveness and help me complete the learning activity quickly.
By expending the same effort as in traditional learning, learning by using a VRH will improve my academic performance.

Effort expectation can be referred by [44]. In the present study, this definition was modified as the degree of ease associated with the use of a VRH for learning. Four items regarding interaction and operations were designed for effort expectation (Table 2).

Table 2. Items of effort expectation

Item
I think the interaction between a VRH and me is clearly comprehensible.
It is easy for me to be proficient in the operation of a VRH.
I think it is easy to learn VRH operation.
It is easy for me to learn VRH operation.

Social influence is defined [44]. In the present study, this definition was modified as the degree to which a student perceives that it is important that others believe he or she should use a VRH for learning. Four items were designed for social influence (Table 3).

Table 3. Items of social influence

Item
Someone who influences my behavior believes that I should learn using a VRH.
Someone important to me believes that I should learn using a VRH.
In general, learning by using a VRH is supported by the school authorities.
In general, learning by using a VRH is supported by teachers.

Finally, facilitating conditions are also defined in [44]. In the present study, it was modified as the degree to which a student believes that the school can support the use of VRHs. Four items regarding resources, knowledge, compatibility, and assistance were designed for facilitating conditions (Table 4).

Table 4. Items of facilitating conditions

Item
I have access to enough resources to use a VRH.
I have enough knowledge to use a VRH
A VRH is incompatible with the learning system that I have been using.
There are specialists who can help me solve operational issues with VRH use.

Behavioral intention is defined as an individual's positive or negative feelings about performing the target behavior [11, 64, 65]. In this study, it was modified as the degree to which a student is willing to use VRH for learning in the near future. Three items were designed for behavior intention (Table 5).

Table 5. Items of behavioral intention

Item
In the near future, I will be very willing to use VRH for learning.
In the near future, I expect myself to use VRH for learning.
In the near future, I will use VRH for learning.

3.3 Research Methods

Data analysis and validation through reliability analysis, validity analysis, and SEM, were performed using AMOS 22. The reliability of the survey results were evaluated using Cronbach α, as is typical for responses on a Likert-type scale. A higher α indicates higher internal consistency. Nunnally et al. suggested that α should at minimum be 0.5 [66]; in empirical studies, α < 0.8 is preferred.

The survey can be validated through such measures as content validity, construct validity, and criterion-related validity. Construct validity was applied in our study and thus both convergent validity (CV) and discriminant validity (DV) were used to evaluate whether our survey results supported our hypotheses. The CV and DV of the different constructs were evaluated by calculating average variance extracted (AVE), composite reliability, and standardized path coefficients (SPC) through confirmatory factor analysis (CFA).

The major steps of SEM analysis, as suggested by Hair et al. [67], were followed in this study. Eight exogenous latent variables ξ and one endogenous variable η were included in our SEM model. Concrete experience (CE), reflective observation (RO), abstract conception (AC), and active experiment (AE) with 12 survey items each were the constructs from Kolb's learning style. Performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC) with four items each were the constructs from the UTAUT. All exogenous latent variables (CE, RO, AC, AE, PE, EE, SI, FC) pointed to the only endogenous latent variable, behavioral intention (BI), which had three items. The structural equation was

$$\eta = \gamma_1 \xi_1 + \gamma_2 \xi_2 + \gamma_3 \xi_3 + \gamma_4 \xi_4 + \gamma_5 \xi_5 + \gamma_6 \xi_6 + \gamma_7 \xi_7 + \gamma_8 \xi_8 + \zeta \qquad (1)$$

where ξ is the exogenous variable, γ is the path coefficient, and ζ is the structural error.

4. RESULTS AND DISCUSSION

Students of National Central University were shown a video on VRH application in learning, following which they were surveyed online. The students were sampled according to the population ratio of the different schools at the university; in total, 387 questionnaires were collected, of which 376 were valid. Table 6 summarizes the statistical descriptions about the sample data. Female students account for 62.2% of all students. Most of the participants amongst the four age groups were in the 21-23-year age group (40.2%), followed by 18-20-year age group (29.8%), and the least were in the 'above 27 years' age group (4.9%). Regarding the education background, 54.8% are undergraduate

students and 42.8% are Master's students. Students from the School of Management and School of Engineering account for more than 50% of the participants.

Table 6. Statistical description of the samples

Variable	Value	Frequency	%
Gender	Male	142	37.8
	Female	234	62.2
Age	18-20	112	29.8
	21-23	151	40.2
	24-26	95	25.3
	≥27	18	4.9
Education	Undergraduate Students	206	54.8
	Master's students	161	42.8
	PhD Students	9	2.4
School	Engineering	83	22.1
	Liberal Arts	32	8.5
	Biotechnology	6	1.6
	Earth Sciences	18	4.8
	Hakka Studies	3	0.8
	Science	55	14.6
	EE & CS	68	18.1
	Management	111	29.5

4.1 Reliability Analysis

First, the importance of the items in the questionnaire was screened through factor loading, which was calculated through CFA. As suggested in [67], items with factor loading > 0.5 were considered important, and the "unimportant" items were removed from the dataset used for the subsequent reliability analysis. The remained items and the Cronbach's corrected α for each construct are summarized in Table 7. The corrected α of most of the constructs were higher than 0.7, except CE and FC [68]; for these two constructs, the corrected α was much higher than 0.35 and thus can be considered acceptable [69]. The overall α as 0.901. The results demonstrate the reliability of the questionnaire.

Table 7. Results of reliability analysis

Construct	Remained Items	Corrected α
CE	3	0.605
RO	5	0.812
AC	6	0.756
AE	8	0.884
PE	4	0.764
EE	4	0.812
SI	3	0.728
FC	3	0.645
BI	3	0.777
Whole	39	0.901

4.2 Validity Analysis

Both CV and DV were used to verify validity analysis in this study. After removing the unimportant items with factor loading <0.5, CR and AVE were used to evaluate CV and DV, respectively. The results of calculated CR and AVE for each construct are summarized in Table 8. Most of the calculated CRs were higher than 0.7, except FC, which nevertheless was nearly 0.7 (0.692); in short, the results reveal that the questionnaire has high CV. Similarly, most AVEs were higher than the suggested threshold of 0.50 [70], except for FC (0.430); nevertheless, FC

was retained in the analysis as it was considered to be sufficiently close to the threshold.

Table 8. Results of CV analysis

Construct	CR	AVE
CE	0.753	0.506
RO	0.904	0.652
AC	0.876	0.541
AE	0.921	0.594
PE	0.850	0.591
EE	0.878	0.648
SI	0.802	0.586
FC	0.692	0.430
BI	0.831	0.623

The results of the DV analysis are summarized in Table 9. The entries along the diagonal line of the table show the calculated AVEs, and those below are the squares of the correlation coefficients of the two intersecting constructs. The discrimination between any two constructs is significant if the square of the correlation coefficient is smaller than the AVE of both constructs. As evident from the table, each construct is valid.

Table 9. Results of DV analysis

	CE	RO	AC	AE	PE	EE	SI	FC	BI
CE	0.506								
RO	0.281	0.652							
AC	0.336	0.176	0.541						
AE	0.250	0.185	0.123	0.594					
PE	0.185	0.063	0.040	0.096	0.591				
EE	0.026	0.053	0.078	0.048	0.160	0.648			
SI	0.109	0.084	0.029	0.053	0.336	0.084	0.586		
FC	0.096	0.068	0.053	0.073	0.137	0.260	0.240	0.430	
BI	0.194	0.078	0.063	0.073	0.436	0.168	0.449	0.250	0.623

4.3 SEM Analysis

Based on the items selected during the reliability analysis, several modifications were applied by freeing parameters that were fixed or fixing parameters that were free, because unacceptable model fit was found in the original structural equation model. Figure 1 shows the modified structural equation model of this study, where BI is the only endogenous latent variable with three items.
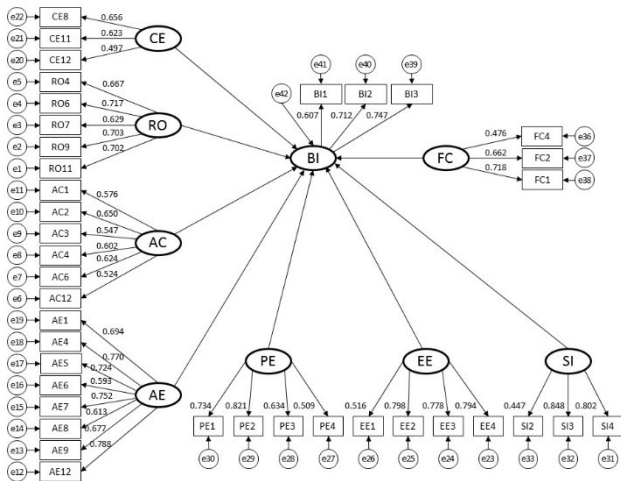
Figure 1. Modified Structural Equation Model

The Bollen-Stine bootstrapping procedure was used to evaluate fit indices. The modified test results for global goodness-of-fit index (GFI) are shown in Table 10. The ratio of the chi-square and degree of freedom is 1.203, which is within the maximum threshold. Moreover, GFI and adjusted GFI (AGFI) are higher than 0.8 and are thus acceptable [71, 72], and the root mean square error of approximation (RMESA) meets the recommended criteria [73]. Besides, both comparative fit index (CFI) and incremental fit index (IFI) are higher than ideal. Hence, the modified structural equation model shown in Figure 1 satisfies the requirements of the goodness of fit for SEM approach.

Table 10. Modified global GFI test results

Fit Index	Criteria	Goodness of Fit
Bollen-Stine χ^2	the less the better	833.601
χ^2/DF	$1 < \chi^2$/DF < 3	1.203
GFI	>0.9	0.863
AGFI	>0.9	0.844
RMSEA	≤ 0.05	0.023
CFI	>0.9	0.974
IFI	>0.9	0.974

Finally, inferences from all exogenous variables to BI were reviewed. Both the SPCs and p values were calculated to verify our hypotheses (Table 11). Hypotheses H_1–H_4 are about the inference between the four constructs of Kolbs' learning styles and the behavioral intention. Our result suggests that only the concrete experience has a significant effect on the behavioral intention to learn when VRHs are used. Hence, if the universities want to promote VRHs for learning, they should also promote students' concrete experience on using VRHs. For example, how to use VRHs to strengthen students' visual impression and responses? How to make an immersive and engaged experience for the students? Developers of the virtual reality learning materials should carefully consider all of the items related to the concrete experience of Kolbs' learning styles. However, we did not find that reflective observation, abstract conception, and active experiment have significant relationships with   behavioral intention. On the other hand, the hypotheses regarding UTAUT and BI are all supported. The results suggest that students believe that using VRHs to learn will help them to improve learning effectiveness and academic performance compared with the

traditional method, therefore, increase their behavioral intention. When students feel easy and proficient in the operation of VRH, their intention of using VRHs for learning will be increased also. The supports from school authorities, teachers, and someone important to students also play important role on their intention of using VRHs for learning.

Table 11. Hypothesis validation

Hypothesis	Path	SPC	p-value	Significant
H_1	CE ➔ BI	0.174	0.011	Yes
H_2	RO ➔ BI	0.012	0.833	No
H_3	AC ➔ BI	0.035	0.554	No
H_4	AE ➔ BI	-0.003	0.953	No
H_5	PE ➔ BI	0.421	<0.001	Yes
H_6	EE ➔ BI	0.168	0.003	Yes
H_7	SI ➔ BI	0.442	<0.001	Yes
H_8	FC ➔ BI	0.165	0.012	Yes

5. CONCLUSIONS

An approach that combines the four UTAUT constructs and Kolb's stages of learning styles was proposed to study the behavioral intention to use VRHs in learning. This approach notably differs from approaches that have combined UTAUT and the big five personality traits. In Kolb's learning style theory, the learning process is classified into four consecutive stages. Initially, the learner engages themselves in concrete experiences (CE), which allow them to reflect on and observe their experiences from many perspectives (RO). Subsequently, the learners abstract the concepts (AC) from experiences and observations to form their own theories, and use these theories to make their own choices in real life (AE). Hypothesis H_1, which states that CE is a significant construct that affects the behavioral intention to use VRHs in learning, was validated, indicating that students intuitively learn from their personal experiences. Because of the limitation, we were unable to implement a real VRH learning experience for the students. Instead, students were shown a video of VRH application in learning and then surveyed online; this approach clearly cannot replicate the real immersion of a VRH experience. According to Kolb's theory, CE is key for the development of the subsequent stages. Probably that's the reason why hypotheses H_2, H_3, and H_4 are not supported.

Regarding the four UTAUT constructs, hypotheses H_5–H_8 are all sustained; in short, all of performance expectancy, effort expectancy, social influence, and facilitating conditions had a significant effect on student behavioral intentions. Thus, students respectively expect an improvement in their academic performance through VRH use, find it simple to use VRHs, note that support from school authorities and instructors would increase their willingness to use VRHs for learning, and note that adequate VRH resources and convenient facilities and infrastructure would increase their willingness to use VRHs for learning.

Our survey only included students of a university in Taiwan, which may induce a homogeneity problem in the results. Future investigations should therefore include students from different schools and countries. In addition, this study mainly focused on user behavioral intention, and the participants had no opportunities to experience real VR immersion; studies involving real VRH experiences could yield more comprehensive findings.

6. ACKNOWLEDGMENTS

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