Luo and Du *Smart Learning Environments* (2022) 9:22
https://doi.org/10.1186/s40561-022-00203-z

Smart Learning Environments

RESEARCH

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Learning with desktop virtual reality: changes and interrelationship of self-efficacy, goal orientation, technology acceptance and learning behavior

Yan Luo and Huan Du*

*Correspondence:
huandu@shu.edu.cn

SHU-UTS SILC Business School, Shanghai University, 20 Chengzhong RD, Shanghai 201800, China

Abstract

With advantages such as ease of use and low cost, desktop virtual reality (VR) technologies are increasingly being used in practical learning. This study aims to clarify the relationship among students' self-efficacy, goal orientation, technology acceptance [e.g., perceived usefulness (PU) and perceived ease of use (PEOU)] and learning behavior, and the changes of these variables as well as gender difference in the early and late stages of course study when desktop VR technology is applied to business simulation learning. A pretest–posttest group design with two repeated measures is employed for this study. During a 10-week period, students' self-efficacy, goal orientation, technology acceptance and learning behavior are measured among junior and senior students majoring in Business Administration from a four-year undergraduate university who used desktop VR technology for practical learning. Course scores for these students are also collected and used to measure whether desktop VR is helping to improve their learning outcomes. Findings indicate that there is a significant correlation between self-efficacy, PEOU, PU and goal orientation, which further affects learners' learning behavior and learning outcomes when desktop VR is used for practical learning. After learning with desktop VR, self-efficacy, perceived ease of use and usefulness, and surface learning behaviors increased, while mastery goal orientation decreased. Furthermore, self-efficacy, PEOU and PU are found to be significantly higher in males than in females.

Keywords: Desktop virtual reality, Self-efficacy, Technology acceptance, Goal orientation, Learning behavior

Introduction

The purpose of practical learning is to enable students to better apply their theoretical knowledge in the real environment. Practice learning and theory learning complement each other, so that students can achieve better learning outcomes. With the continuous progress of science and technology, an increasing number of new digital devices and applications have been used for the purpose of practical learning (Zawacki-Richter & Latchem, 2018). Among these new technologies, devices and applications based on desktop virtual reality (VR) technology are gradually valued and applied in different educational domains (Radianti et al., 2020).

Desktop VR technology has been widely utilized in learning. Currently, many learning systems based on desktop VR technology have emerged around the world and a large number of learners are using them. Labster is one of the most well-known and widely used desktop VR platforms, offering a variety of different desktop VR systems for learners around the world. According to the data from it, up to March 2022, Labster has provided virtual lab products to more than 5 million students from high schools and universities around the world. It has developed different desktop VR products for 39 major professional categories and has been used by more than 2,000 institutions and schools. In addition, according to the data from ilab-x, another large desktop VR platform, in November 2020, there were 353 national virtual simulation laboratory teaching programs in China. One year later, the number of national virtual simulation experimental teaching projects grew to 687. The annual growth rate reached 94.61%. According to the site, the most popular desktop VR system experiment has had more than 250,000 experiment visits, and the second and third most popular ones both have more than 100,000 visits. All data suggest that desktop VR technology is being used more and more extensively in education. Therefore, this study investigates whether learning with desktop VR technology can enhance learners' learning outcomes.

With the advantages and rapid development of desktop VR technology, it has been widely applied in different areas of education. As displayed in Table 1, many scholars have studied the application of desktop VR systems in different domains. For example, Makransky and Petersen (2019) analyzed the relationship between VR features, presence, self-efficacy, knowledge and other variables of 199 first-year medical undergraduates when using a desktop VR system called *medical genetics simulation*. Barrett and Blackledge (2013) analyzed the relationship between variables such as immersion, perceived usefulness (PU), perceived ease of use (PEOU), presence, motivation of 87 final year undergraduate students studying electricity when using a desktop VR called 'VES'.

Through the review and analysis of all the articles in Table 1, we can conclude that there is almost no research regarding changes in students' self-efficacy, goal orientation, technology acceptance and learning behavior before and after VR technology is used, and few scholars have studied the effectiveness of desktop VR systems in business learning. In business learning, it is impractical for learners to directly participate in the actual business decisions. The application of desktop VR technology enables business students to experience simulated business operations and the decision-making process before entering the workplace. Therefore, it is of practical importance to take desktop VR technology into business learning. Hence, this research aims to analyze the relationship among students' self-efficacy, goal orientation, technology acceptance (e.g., PEOU and PU), learning behavior and learning outcome, so as to clarify whether the use of desktop VR technology can enhance learners' learning outcomes. Besides, this research also measures the changes of these variables as well as gender difference in the early and late stages of the course study when desktop VR technology is applied in business simulation learning.

Table 1 A selected review of research on desktop VR technologies in different application domain

Article	Application domain	Desktop VR technologies	Research variable	Method
Makransky et al. (2019)	Biology	A bacterial isolation virtual lab simulation	Perceptions of assessment; INTRINSIC MOTIVATION; SELF-EFFICACY; TRANSFER	Paired samples t-tests
Lee and Wong (2014)	Biology	A desktop VR program called 'V-Frog™'	Performance achievement; spatial ability; learning mode	Descriptive statistics
Lee et al. (2010)	Biology	A desktop VR program called 'V-Frog™'	VR features; PU; PEOU; presence; motivation; learning outcomes	SEM analysis
Merchant et al. (2012)	Chemistry	Second Life	VR features; usability; self-efficacy; learning outcome	SEM analysis
Wang et al. (2018)	Construction	Desktop-based VR, immersive VR		Summary
Blackledge and Barrett (2013)	Electricity	Prototype model 'VES'	Immersion; PU; PEOU; motivation; intention to use; satisfaction	Case study
Hoffmann et al. (2006)	Engineering	A small VR system called 'PI-casso'		Experiment
Piccoli and Ives (2001)	IT	A curriculum delivery application called 'lotus learning space'	Time; place; space; interaction; technology; learner control	Descriptive Statistics
Kebritchi et al. (2010)	Mathematics	A set of mathematics instructional games called Dimension™		Experiment
Pasqualotti and Freitas (2002)	Mathematics	A virtual environment called 'MAT^{3D}'	Performance	Case study
Makransky and Petersen (2019)	Medicine	Desktop VR medical genetics simulation	VR features; PE; active learning; intrinsic motivation; self-efficacy;	SEM analysis
Makransky et al. (2020)	Medicine	A genetics simulation developed by Labster	Intrinsic motivation; self-efficacy; transfer	Paired samples t-tests
Dubovi et al. (2017)	Nursing	The pharmacology inter-leaved learning VR	Learning outcome (course score)	Descriptive statistics

Desktop virtual reality

Virtual reality refers to "a specific type of reality simulation system constructed by the combination of hardware and software systems" (Biocca & Delaney, 1995). Depending on the level of immersion provided by VR equipment, VR technology can be categorized as immersive VR and non-immersive VR (Radianti et al., 2020). When using immersive VR devices, users feel like they are immersed in a virtual world and do not perceive that they are interacting with a screen and a set of devices. Example of such VR technology includes HMDs (head-mounted displays) such as HTC Vive and enhanced VR such as data gloves (Khalifa & Shen, 2004; Martín-Gutiérrez et al., 2017). On the contrary, when using non-immersive VR devices, users can still perceive that they are looking at a screen or interacting with the devices. The most commonly used non-immersive VR is desktop VR system (Biocca & Delaney, 1995; Robertson et al., 1997). Desktop VR is a non-immersive VR consisting of a personal computer and software applications that can be interacted with by using common devices such as a keyboard and mouse (Ausburn & Ausburn, 2004; Chen et al., 2004; Lee & Wong, 2014).

Immersive VR and non-immersive VR have their own advantages and disadvantages, and therefore can be applied to different contexts. Immersive VR has the characteristics of high immersion, so it has the potential to maximize learning efficiency. However, immersive VR also has many disadvantages in practice. First of all, long-term use of immersive VR devices may cause users to experience symptoms such as dizziness, nausea and vomiting dizziness. Secondly, the high equipment and maintenance costs of immersive VR prevent it from being widely used in practice learning (Chuah et al., 2010; Lee & Wong, 2014; Merchant et al., 2014). Dalgarno et al. (2002) suggest that "immersion in virtual environment is caused by user's control over environment, interaction with the environment, not just the nature of the environment itself". Although it cannot make users experience complete immersion, non-immersive VR such as desktop VR also has its incomparable advantages. With the rapid iteration of computer chips and network technology, many desktop VR software was introduced, allowing users to use their personal computers or mobile phones to access desktop VR system whenever and wherever they want, which increases the convenience of using the technology (Dickey, 2005). Besides, compared with immersive VR, desktop VR has lower use and maintenance costs, which makes it more likely to be widely used (Srivastava et al., 2019).

Hypotheses and research questions

Self-efficacy, PEOU and PU

Self-efficacy is defined as an individual's confidence in his or her own ability to perform the actions needed to achieve the desired results (Bandura, 1982). Aftab et al. (2012) pointed out that self-efficacy is related to personal accomplishment. In general, strong sense of self-efficacy has been shown to be related to high level of personal accomplishment (Bandura, 1999; Zimmerman, 2000). Individuals with a strong sense of self-efficacy regard difficult tasks as challenges and are willing to accomplish them through their own efforts. Besides, they have also been found to be more able to focus on the tasks. Even when encounter failure, they can deal with it calmly and learn from the experience to improve themselves.

Previous studies have considered that learners' self-efficacy in VR learning environment affects the construction of TAM model. Specifically, self-efficacy may have an impact on PEOU and PU (Chow et al., 2012; Grandon et al., 2005). Through meta-analysis of 41 studies, Abdullah and Ward (2016) summarized the relationship between self-efficacy, PEOU and PU. The findings showed that 41 studies confirmed the positive link between self-efficacy and PEOU. However, considering the connection of self-efficacy and PU, only 10 studies show that self-efficacy has a positive impact on PU, and 17 studies show that the correlation between them is not significant. In order to further verify whether self-efficacy affects students' perceived ease of use and perceived usefulness of the desktop VR system, this research puts forward the following hypotheses:

H1 Self-efficacy has a positive effect on perceived usefulness of desktop VR system.

H2 Self-efficacy has a positive effect on perceived ease of use of desktop VR system.

Self-efficacy and goal orientation

In the past 45 years, goal orientation theory has emerged as an essential research direction for the area of achievement motivation, especially academic motivation. Goal orientation is the situational orientation of action in achievement related tasks (Malouff et al., 1990). It does not focus on what people try to achieve (i.e., targets and specific criteria), but defines why and how people try to accomplish different goals (Anderman & Maehr, 1994).

According to the two dimensions of performance and mastery and the two directions of approach and avoidance, Elliot and Mcgregor (2001) divided goal orientation into four aspects: performance approach, performance avoidance, mastery approach and mastery avoidance. Mastery goal orientation is an individual's goal of self-development and growth (Ames, 1992). Mastery oriented students attach great importance to learning, understanding and mastering new knowledge or skills. According to the two dimensions of approach and avoidance, mastery goal orientation can then be divided into mastery approach and mastery avoidance. Performance goal orientation is an individual's goal of accomplishing tasks and being praised and approved from others (Ames, 1992). Different from mastery oriented students, students who are performance-oriented may pay more attention to the completion of tasks and performance related outcomes, such as exam scores and course results. According to the two dimensions of approach and avoidance, performance goal orientation can be categorized into performance approach and performance avoidance.

The relationship between self-efficacy and goal orientation has been discussed by many scholars. In accordance with social cognitive theory, individual's self-efficacy can affect many aspects of their life, for example, their goal setting (Bandura, 1989). In addition, Stevens and gist (1997) also put forward the view that self-efficacy has an impact on the choice of a specific goal orientation. This statement was further confirmed in some other researches. Some researches suggested that self-efficacy was positively related to mastery goal orientation and performance approach goal orientation, and negatively related to performance avoidance goal orientation (Diseth, 2011; Kaplan & Midgley, 1997; Sanusi et al., 2018). Fenollar et al. (2007) proposed that high self-efficacy is positively related to mastery approach and Performance approach goal orientation; on the contrary, low self-efficacy is positively related to mastery avoidance and performance avoidance goal orientation. Jiang et al. (2014) considers that self-efficacy and goal orientation are associated with specific situations. This suggests that individual's self-efficacy and goal orientation may vary in different situations. Although the relationship between self-efficacy and goal orientation has been extensively studied in existing research, few scholars have attempted to investigate the association between self-efficacy and goal orientation when desktop VR systems are used. Therefore, this study puts forward the following hypothesis:

H3 Self-efficacy is positively related to a specific goal orientation in the context of using desktop VR system.

PEOU, PU and learning behavior

Learning is the acquisition of knowledge or skills through reading, listening, research, practice, etc. (Washburne, 1936). Learning behavior is a specific behavior taken by individuals in the process of learning. Biggs (1987) divides students' learning behaviors into deep and surface learning behavior. Deep learning behavior is manifested in learners' active participation, attention to knowledge structure and use of critical thinking and deep thinking. Surface learning behavior reflects that learners' cognitive level stays at the superficial level, including simple reading and memorizing, surface thinking and even no thinking.

Learners' learning behaviors might be affected by many factors. According to TAM model, PEOU and PU influence users' behavior intention and further influence users' behavior (Fagan et al., 2012; Fokids, 2017; Saritas, 2015). The results of these studies suggest that PU and PEOU lead to different learning behaviors when various educational technology systems or platforms are used for learning. However, few studies have examined the relationship between these variables when desktop VR is used for learning. Therefore, in order to verify whether PEOU and PU affect the choice of students' specific learning behavior when desktop VR system is used, this study puts forward the following hypothesis:

H4 Perceived usefulness of desktop VR system affects learning behavior.

H5 Perceived ease of use of desktop VR system affects learning behavior.

Goal orientation and learning behavior

In addition to self-efficacy and technology acceptance, goal orientation may also have an impact on learners' learning behaviors (Yokoyama and Kazuhisa, 2020). Therefore, students with different goal orientation may perform different learning behaviors. Fenollar et al. (2007) proposed that students with mastery goal orientation hope to obtain new knowledge or skills from learning. These students, therefore, often adopt deep learning behaviors in their learning process. However, Tang and Bhamra (2012) pointed out that students with high learning expectations may not show deep learning behaviors. In addition, Geitz et al. (2016) found out that learners with mastery approach goal orientation may also adopt surface learning behaviors. From the existing research results, the connection between goal orientation and learning behavior is still not clear enough. Mastery oriented learners may show both deep and surface learning behaviors. For learners with performance orientation, they may also take deep learning behaviors in order to achieve good performance. In addition, although desktop VR has been increasingly used in teaching and learning, few studies have been done to examine the relationship between students' goal orientation and learning behavior when desktop VR technology is used for learning. Therefore, in order to fill the gap, this study puts forward the following hypothesis:

H6 Specific goal orientation is related with different learning behaviors.

Learning behavior and learning outcome

When students exhibit different learning behaviors, their learning efficiency and effectiveness will be different. As a result, their learning outcomes will also vary. Existing research suggests that when students exhibit deep learning behaviors, they are more actively engaged in course content and demonstrate critical thinking and deeper reflection, and these deep learning behaviors lead to better learning outcomes; in contrast, when learners exhibit surface learning behaviors, they will spend less time studying and will learn less effectively, and therefore, will have poorer learning outcomes (Goh, 2005; Magdalena, 2015). To verify whether students' learning behaviors affect their learning outcomes when desktop VR is used for learning, this study proposes the following hypothesis:

H7 Different learning behaviors is related with different learning outcomes.

Research model

On the basis of the seven hypotheses mentioned above, a theoretical model is proposed in this study (Fig. 1). Self-efficacy is considered to have an impact on PU, PEOU, and goal orientation of students who are using the desktop VR system, which further influences the learning behaviors exhibited by these students. Learning behaviors further result in different learning outcomes.

Review of research on changes of variables and gender difference

Individuals will always modify their attitudes and behaviors in order to cope with different situations. Social cognitive theory points out that self-efficacy can change through

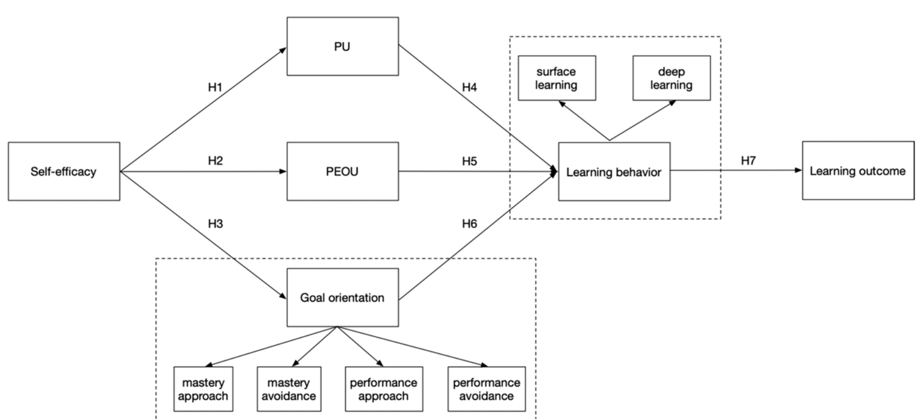

Fig. 1 Proposed research model

successful practical experiences, alternative experiences, verbal persuasion, and the influence of physical and mental states, thus suggesting that self-efficacy is dynamic and cultivable (Mathieu et al., 1993). In addition, cognitive dissonance theory suggests that when users are cognitively dissonant and in a state of imbalance, this sense of dissonance may lead them to adjust or re-judge their beliefs, attitudes and behaviors (Festinger, 1957). Research on desktop VR technology in recent years has also indicated that learners' self-efficacy and intrinsic motivation change significantly after using desktop VR for learning (Makransky et al., 2020). Thus, whether experiencing intentional positive nurturing or cognitive dissonance, self-efficacy may change, leading to changes in students' attitudes, behaviors, and other factors. DeShon and Gillespie (2005) argue that an individual's choice of goal orientation is a combined examination of the current situation and personal achievement. Depending on the specific situation and the individual's achievement level, individuals may exhibit different goal orientations. For example, if an individual deems that the current task is important for his or her future development and he or she has previous experience in completing similar tasks, then the individual is likely to exhibit a goal orientation of mastery approach. Conversely, if a person does not consider the current task to be directly related to his or her future development and only wants to spend a minimum amount of time on the task, then the person is likely to exhibit a performance avoidance goal orientation.

Besides self-efficacy and goal orientation, studies have also shown that PU and PEOU change over time. Belief renewal theory states that users adjust their perceived usefulness and perceived ease of use towards a system as they use it over time (Venkatesh, 2000). In other words, with increasing time of use, the perceived usefulness and ease of use of an individual may change. Student learning behavior is influenced by many factors, such as technology acceptance, self-efficacy and goal orientation. Therefore, if these factors change, the learning behaviors exhibited by students may change as well.

Existing studies have tried to examine the changes in many different variables over time. From Table 2, it can be seen that Maltinsky and Swanson (2020) measured behavioral change among diabetes practitioners through pre and post measures with a time interval of 6 weeks. Geitz et al. (2016) measured changes in self-efficacy, goal orientation, and learning behaviors of students in a PBL group over an eight-week period of a semester. In addition, Cheng (2014) and Hogan et al. (2020) analyzed how PEOU and PU change in the short term when a new technology is used. Existing studies have examined how self-efficacy, goal orientation, and technology acceptance and behavior change over time for different individuals; however, few studies have been found that analyze how these variables change during learning with desktop VR technology. To fill this research gap, this research puts forward the following research questions:

RQ1 Do self-efficacy, PU, PEOU, goal orientation, and learning behaviors of students change over time when using desktop VR technology, and if so, what is the direction of change?

Moreover, there may be gender differences in the attitudes and behaviors exhibited by individuals when desktop VR is used for learning due to factors such as differences in thinking styles and personalities. Some research considers that there may be

Table 2 A selective review of research on behavior change or attitude change

Article	Variable	Theory	Measurement times
Emirza and Şengönül (2021)	General self-efficacy and Job search self-efficacy	Social cognitive theory	2 times
Hogan et al. (2020)	PU, PEOU, subjective norm, job relevance and intention to use	NA	2 times
Ke et al. (2020)	Technology acceptance and behavioral engagement	NA	2 times
Maltinsky and Swanson (2020)	Motivation and behavior	Dual Process Theory	2 times
Harari et al. (2017)	Activity and sociability behaviors	NA	3 times
Asensio and Delmas (2016)	Conservation behavior	NA	2 times
Geitz et al. (2016)	Self-efficacy, goal orientation, learning behavior	NA	3 times
Mou et al. (2017)	PU, trust in provider, confirmation, intention, subjective norm, satisfaction and actual usage	Expectation-confirmation theory	2 times
Ng and Lucianetti (2016)	Organizational trust, perceived respect, self-efficacy and innovative behavior	Social cognitive theory	3 times
Cheng (2014)	PU, PEOU, perceived enjoyment and intention to use	NA	2 times
Cranen et al. (2011)	Performance expectancy, effort expectancy, social influence and intention to use	NA	2 times

discrepancies between men and women in terms of self-efficacy and goal orientation (Broos, 2005; GM D'Lima et al., 2014). Moreover, some studies have shown that men and women differ in their technology acceptance, so people of different genders may exhibit different levels of perceived ease of use and usefulness (Emin & Sami, 2016; Ong & Lai, 2006). To understand whether students of different genders exhibit different self-efficacy, goal orientation, technology acceptance, and learning behaviors when desktop VR is used for learning, this research proposes research question:

RQ2 Do students of different genders exhibit different levels of self-efficacy, goal orientation, technology acceptance and learning behaviors when using desktop VR?

Methodology

Context

A course called Business Decision Simulation from SHU-UTS SILC Business School, Shanghai University was selected for this study. The course is offered in the third year of the undergraduate business administration program and lasts for 10 weeks. It was conducted using a desktop virtual simulation system called *CESIM Global Challenge*, in which students were required to form a team of four or five people to virtually run the business of a multinational company. At the end of the 10-week course, each team was ranked according to 10 rounds of business simulation. This course is designed to help management students understand and learn how to make corporate decisions in a dynamic business environment.

Participants

Participants of this study are 94 junior and senior students majoring in Business Administration from SILC Business School of Shanghai University (N = 94; 26 males, 68 females).

Instruments

The questionnaire used in this study is composed of four sub-questionnaires with a total of 44 questions, all of which have been used in existing studies to measure college students.

Self-efficacy was measured with the translated new general self-efficacy (NGSE) scale, which is a 5-point Likert scale consisting of 8 question items (Chen et al., 2001). The Cronbach's α value was 0.86.

PU and PEOU was measured using a sub-questionnaire from a TAM scale, which is a 5-point Likert scale consisting of 8 question items (Venkatesh, 2000). The Cronbach's α values were 0.87 for PU and 0.86 for PEOU.

A translated version of the validated Achievement Goals Questionnaire was adapted to measure students' goal orientation (Elliot & McGregor, 2001), which is a 5-point Likert scale consisting of 12 items with each of the four goal orientations consisting of three questions. The Cronbach's α values were 0.87 for mastery approach, 0.89 for mastery avoidance, 0.92 for performance approach and 0.83 for performance avoidance.

A translated version of the R-SPQ-2F was adapted to measure students' learning behavior (John et al., 2001). this scale is a 5-point Likert scale consisting of 20 items, with 10 question items for deep and surface learning approach, respectively. The Cronbach's α values were 0.73 for deep learning approach and 0.64 for surface learning approach.

Data collection procedure

Students' self-efficacy, goal orientation, technology acceptance, and learning behavior are obtained through questionnaire research. In the second class of the first week (time point A), the course instructor first introduced the basic information and rules of the VR system to all students, and then asked them to form groups. Each group needed to determine their company name, slogan, and each individuals' role in the company. After that, the course assistant distributed the questionnaire and took the first measurement. In the last course of the tenth week (time point B), when all course instruction has been completed and the simulation is finished, a questionnaire is distributed by the course assistant for a second measurement.

Student's learning outcomes are measured by the final score of the Business Decision Simulation course, as course scores are the most accurate and quantitative indicator that can reflect students' learning outcomes directly. The total score is 100 points which is composed of students' course participation score, simulated decision making score, and presentation score.

Data analysis

Descriptive statistical analysis was used to get a basic overview of the sample. The scales all passed a reliability test (Cronbach's alpha). Paired sample T tests were conducted to determine if there were statistically significant differences between different goal orientation, self-efficacy, PU, PEOU and learning behaviors in the early and late stages of the ten weeks of study. The relationships between variables were determined by correlation analysis. Independent sample t-tests were conducted to reflect differences in variables between genders.

Results

The reliability of each scale at time point A and B is shown in Table 3. All scales had Cronbach's alphas greater than 0.7 at both time points, which indicates good reliability of the scales.

Changes of variables over time

The means and standard deviations of the variables at time point A and B are shown in Table 4. The tested student group exhibited high level of self-efficacy at time point A and B (M = 3.98; 4.15). For goal orientation, compared with the scores on the variables of performance avoidance (M = 3.48; 3.16) and mastery avoidance (M = 3.44; 3.28), the tested sample showed higher levels of performance approach (M = 3.91; 3.88) and mastery approach (M = 4.11; 3.83). In addition, PU and PEOU was reported on an below average level at time point A (M of PU = 3.75; M of PEOU = 3.50), while both scores increased at time point B(M of PU = 4.00; M of PEOU = 3.78). For learning behaviors, the respondents showed moderate levels of deep learning behaviors (M = 3.70; 3.71) and lower levels of surface learning behaviors (M = 2.81; 3.07) on both time point A and B. Learning outcomes were measured by the students' course grade, with an average score of 86.38 for all students involved in the study.

Paired-sample t-tests were used to determine whether the variables were significantly different after ten weeks of learning using desktop VR. The results of the paired-samples t-test are provided in Table 5. Significant increase in students' self-efficacy, PEOU and PU occurred from time point A to B. For goal orientation, mastery

Table 3 Cronbach's alpha at time point A and B

Measurement	A	B	Items
Self-efficacy	.864	.888	8
Goal orientation			
Performance-approach	.898	.848	3
Performance-avoidance	.812	.792	3
Mastery-approach	.841	.755	3
Mastery-avoidance	.740	.755	3
PEOU	.794	.808	4
PU	.874	.818	4
Learning behavior			
Deep learning	.887	.897	10
Surface learning	.818	.822	10

Table 4 Means and standard deviations of the variables (5-point scale) at time point A and B

	A		B	
	M	SD	M	SD
Self-efficacy	3.98	.53	4.15	.57
Goal orientation				
Performance-approach	3.91	.75	3.88	.81
Performance-avoidance	3.48	.84	3.16	.90
Mastery-approach	4.11	.61	3.83	.66
Mastery-avoidance	3.44	.82	3.28	.79
PEOU	3.50	.71	3.78	.68
PU	3.75	.66	4.00	.62
Learning behavior				
Deep learning	3.70	.58	3.71	.61
Surface learning	2.81	.58	3.07	.62
Learning outcome			86.38	5.14

Table 5 Paired sample T test of variables from time point A to B

	Time point	M	SD	t	df	*p*
Self-efficacy	A	3.98	.53	− 2.227	93	.028**
	B	4.15	.57			
Goal orientation						
Mastery-approach	A	4.11	.61	2.914	93	.004*
	B	3.83	.66			
Mastery-avoidance	A	3.44	.84	3.310	93	.001*
	B	3.03	.90			
PEOU	A	3.50	.71	− 2.790	93	.006*
	B	3.78	.68			
PU	A	3.75	.66	− 2.640	93	.010*
	B	4.00	.62			
Learning behavior						
Surface learning	A	2.81	.59	− 2.960	93	.004*
	B	3.07	.62			

*Significant at a confidence level of $p < 0.025$ (2-tailed)

**Significant at a confidence level of $p < 0.05$ (2-tailed)

approach and mastery avoidance decreased significantly, while performance approach and performance avoidance did not change significantly. Surface learning behaviors decreased significantly from time point A to B, while no significant changes occurred for deep learning behaviors.

The relationships between variables

Correlation analysis was used to analyze the relationship between self-efficacy, different goal orientations, PEOU, PU, and learning behaviors.

As shown in Table 6, self-efficacy is positively related to performance approach and mastery approach goal orientations at both time points A and B, and positively related

Table 6 Significant relationships between the concepts at time point A and B

Measurement	Time point	r_S
Self-efficacy—goal orientation		
Self-efficacy—performance-approach		
	A	.427*
	B	.487*
Self-efficacy—performance-avoidance		
	A	.273*
Self-efficacy—mastery-approach		
	A	284*
	B	.387*
Self-efficacy—PEOU		
	A	.287*
	B	.324*
Self-efficacy—PU		
	A	.330*
	B	.446*
Goal orientation—Learning behavior		
Performance-approach—Deep learning		
	A	.474*
	B	.467*
Mastery-approach—deep learning		
	A	.677*
	B	.441*
Performance-avoidance—surface learning		
	A	.518*
	B	.491*
Mastery-approach—surface learning		
	A	− .268*
	B	− .239*
Mastery-avoidance—surface learning		
	A	.457*
	B	.366*
PEOU—learning behavior		
PEOU—deep learning		
	A	.211**
	B	.468*
PEOU—surface learning		
	B	.213**
PU—learning behavior		
PU—deep learning		
	A	.395*
	B	.589*
Learning behavior—learning outcome		
Deep learning—learning outcome		
	B	.312*
Surface learning—learning outcome		
	B	− .263**

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

**Correlation is significant at the 0.05 level (2-tailed) to performance-avoidance goal orientation at time point A. In addition, self-efficacy showed significant positive correlations with PEOU and PU at both time points.

For the relationship between goal orientation and learning behavior, performance approach and mastery approach are positively correlated with deep learning behavior at both time point A and B, performance avoidance and mastery avoidance are positively correlated with surface learning behavior, while mastery approach is negatively correlated with surface learning behavior at two time points. The correlation between PEOU and deep learning is significant at both time points, and the correlation between PEOU and surface learning behavior is significant only at time point B; PU showed positive correlation with deep learning behavior at A and B, but not significant correlated with surface learning behavior.

The results of the correlation analysis also showed that students' learning behaviors affect their learning outcomes. Deep learning behaviors positively affect their learning outcomes, while surface learning behaviors negatively affect their learning outcomes.

Gender differences between variables

Independent samples t-tests were conducted to compare the variables on gender (see Table 7).

There were significant differences between the mean scores of men and women in terms of self-efficacy, PEOU and PU. Specifically, men showed higher levels of self-efficacy and PU than women at both time points A and B. Moreover, at time point A, PEOU was also significantly higher for men than for women, while this significant relationship disappeared at time point B.

Conclusions and discussion

Seven hypotheses and two research questions were formulated in this study. These hypotheses and research questions were confirmed and answered by collecting questionnaires and analyzing the data. Hypotheses formulated namely:

H1 Self-efficacy has a positive effect on perceived usefulness of desktop VR system.

H2 Self-efficacy has a positive effect on perceived ease of use of desktop VR system.

Table 7 Significant differences with respect to gender

	Men		Women		t	df	p
	M	SD	M	SD			
Self-efficacy							
A	4.23	.56	3.88	.50	2.737	40	.009
B	4.40	.64	4.06	.52	2.447	38	.019
PEOU							
A	3.79	.83	3.39	.63	2.523	92	.013
PU							
A	4.07	.74	3.63	.59	2.731	37	.010
B	4.25	.65	3.91	.59	2.345	41	.024

H3 Self-efficacy is positively related to a specific goal orientation in the context of using desktop VR system.

H4 Perceived usefulness of desktop VR system affects learning behavior.

H5 Perceived ease of use of desktop VR system affects learning behavior.

H6 Specific goal orientation is related with different learning behaviors.

H7 Different learning behaviors is related with different learning outcomes.

The results of the hypotheses validation are shown in Table 8.

H1 and H2 were confirmed at both time points A and B. The results of the correlation analysis showed that self-efficacy was positively associated with perceived ease of use and perceived usefulness at both time points A and B.

H3 was partially confirmed. It was found that Self-efficacy was significantly and positively related to performance approach, performance avoidance, and mastery approach goal orientations at time point A, and correlated with performance approach and mastery approach at time point B.

H4 was partially confirmed by the significant positive correlation between PEOU and deep learning at time points A and B and the correlation with surface learning at time point B.

Table 8 Research hypotheses results

	Independent variable	Dependent variable	Time point		Conclusion
			A	B	
H1	Self-efficacy	PU	.330*	.446*	Confirmed
H2	Self-efficacy	PEOU	.287*	.324*	Confirmed
H3	Self-efficacy	Goal orientation			Partially confirmed
	Self-efficacy	Performance approach/avoidance	.427*/.273*	.487*/.141	
	Self-efficacy	Mastery approach/avoidance	.284*/.032	.387*/−.138	
H4	PU	Learning behavior (Surface/Deep approach)	− .198/.395*	−.001/589*	Partially confirmed
H5	PEOU	Learning behavior (Surface/Deep approach)	−.085/.211*	.213**/.468*	Partially confirmed
H6	Goal orientation	Learning behavior (Surface/Deep approach)			Confirmed
	Performance approach/avoidance	Surface approach	−.202/.518*	−.109/.491*	
	Performance approach/avoidance	Deep approach	.474*/−.053	.467*/−.100	
	Mastery approach/avoidance	Surface approach	−.268*/.457*	−.239**/.366	
	Mastery approach/avoidance	Deep approach	.677*/.104	.441*/−.155	
H7	Learning behavior (Surface/Deep approach)	Learning outcome		−.263**/.312*	Confirmed

H5 was partially confirmed by the results of the correlation analysis which indicated that PU was significantly correlated with surface learning at both time points A and B but not significant correlated with deep learning behavior.

H6 was confirmed by the significant positive correlations between approach goal orientations and deep learning behavior and between avoidance goal orientations and surface learning behavior. Besides, a negative correlations between mastery approach and surface learning had been found.

H7 was confirmed by the significant positive correlations between deep learning behavior and learning outcome as well as the significant negative correlations between surface learning behavior and learning outcome.

RQ1 Do students' self-efficacy, PU, PEOU, goal orientation, and learning behaviors change over time when using desktop VR technology, and if so, what is the direction of change?

Results of paired-sample t-tests indicated that students' self-efficacy, mastery goal orientations, technology acceptance (PEOU and PU) and surface learning behaviors change over time when desktop VR is used for learning. Significant increases in self-efficacy, technology acceptance, and surface learning behaviors and significant decreases in mastery goal orientations have been found. However, performance goal orientations and deep learning behaviors had not changed over time.

RQ2 Do students of different genders exhibit different levels of self-efficacy, goal orientation, technology acceptance, and learning behaviors when using desktop VR?

The results of independent samples t-test showed that there were significant differences in self-efficacy and technology acceptance between males and females. At both time points A and B, males show higher self-efficacy and PU than females. PEOU is also higher in males than females at time point A. No significant difference in goal orientations, learning behaviors between males and females was found.

Changes and relations of variables during the use of desktop VR

Self-efficacy, goal orientations, technology acceptance (PEOU and PU), and learning behaviors all changed before and after desktop VR is used for learning. In addition to the changes in the variables themselves, the interrelationships between these variables also changed.

First, students' self-efficacy increased significantly after using desktop VR, but performance avoidance goal orientation did not change, which led to a change in the relationship between these two variables. A significant positive correlation between self-efficacy and performance avoidance goal orientation was found at time point A, but this correlation was no longer significant after ten weeks of study.

Second, both PEOU and surface learning behaviors increased significantly after using the desktop VR for ten week. No significant correlation existed between PEOU and surface learning behaviors at time point A, but a significant positive correlation was found at time point B.

Possible explanations for these changes in a short time span are the students' perceptions and attitudes toward the learning environment and course requirements, and the regulation of their own behavior in response to these objective conditions. In this study, self-efficacy was positively related to approach goal orientations, which in turn was positively related to deep learning behaviors. This fits with the results of related studies which indicate that students with high self-efficacy are more probable to become active participants (i.e., develop a mastery approach and/or performance approach goal orientation) and exhibit positive learning behaviors that may lead to good learning outcomes (Caraway et al., 2010; Elliot, 1999).

The current study showed that there was a significant positive correlation between self-efficacy and technology acceptance, and technology acceptance then have a positive impact on deep learning behavior. This is in agreement with the findings of some earlier studies. Chen et al. (2001) suggested that individuals with high self-efficacy are more willing to try and learn a new system or device and exhibit higher level of perceived ease of use and perceived usefulness. Furthermore, Zheng and Li (2020) pointed out that self-efficacy affects users' technology acceptance, which further influences their intention to use as reflected in deep learning behavior.

Besides, this research also found that different learning behaviors result in different learning outcomes. Goh (2005) proposed that deep learning behaviors are positively associated with positive learning outcomes and surface learning behaviors are negatively associated with learning outcomes. Magdalena (2015) suggested that deep learning behaviors are associated with high performance. Consistent with these studies, the present study found that learners' deep learning behaviors are positively associated with learning outcomes and surface learning behaviors are negatively associated with learning outcomes. This result suggests that differences in learners' learning behaviors have an impact on their learning outcomes when learning with desktop VR.

In short, learners' learning strategies are constantly adjusted as learners' self-efficacy, technology acceptance, and goal orientation change. Liem et al. (2008) argued that students choose to change their learning strategies when they believe they can achieve the same or even higher scores when they switch from deep learning strategies to surface learning strategies, and vice versa. Students' self-efficacy, goal orientation, and learning behaviors change as they become familiar with environmental and curricular requirements. Therefore, it is essential that educators are aware of how students' self-efficacy, goal orientation, and learning behaviors change over a relatively short time span, especially over a course cycle. In addition, for courses that require the use of desktop VR systems for learning, system developers need to provide students with some guidance and basic instruction to help them become familiar with the system and enter the learning process more quickly, as acceptance of the VR system enhances students' learning behaviors and further enhances their learning outcomes.

Gender difference and self-efficacy, PEOU and PU

In the present study, male and female students showed significant differences. According to the results of the independent samples t-tests in Table 7, Males scored significantly higher than females on self-efficacy, PEOU and PU. This is consistent with the results of some earlier studies. Numerous studies on self-efficacy have found that females' self-efficacy can be slightly lower than that of males (Turner & Schieman, 2008). Ong and Lai (2006) have shown that males scored significantly higher than females on computer self-efficacy, perceived usefulness, perceived ease of use. In line with this research, Yukun et al. (2013) also confirmed the differences between males and females in self-efficacy and perceived ease of use.

Social and status differences associated with both females and males may explain the gender differences in self-efficacy (Ma et al., 2015; Schwarzer et al., 1999). Such innate gender differences and social status distinctions can lead to cognitive differences between males and females. Females may be more susceptible to stress, less able to cope with their environment, and therefore more likely to experience negative emotions. Males, on the other hand, are relatively more ambitious and independent and therefore exhibit a higher sense of self-efficacy. The difference in self-efficacy further influences the difference in technology acceptability between men and women.

In addition, the differences between self-efficacy, and technology acceptance between men and women may also be caused by differences in thinking patterns between men and women. Men may show higher interest and greater receptivity when using a new system or technology (Braak, 2004; Schumacher & Morahan-Martin, 2001; Teo & Lim, 1996). However, differences between men and women were not found in goal orientation and learning behavior. This suggests that there are no significant differences in goal orientation and learning behaviors between genders when desktop VR is used for learning, and that high scores in self-efficacy and technology acceptance among males do not result in different goal orientation and learning behaviors compared to females. A better understanding of gender differences in user attitudes toward desktop VR systems could help researchers consider gender factors when developing and testing desktop VR learning systems in the future. In addition, administrators and tutors can become aware that the same desktop VR system may be perceived in a different way depending on gender and then improve user acceptance by making targeted adjustment of the course schedule and content.

Limitations and future research

This study contributes to the continuously increasing research on self-efficacy, goal orientation, technology acceptance, and learning behavior. particularly in environments using desktop VR, as much of the research is conducted in more conventional course environment. Nevertheless, this study has some limitations that have to be considered. Firstly, the relatively small sample size of this study does not allow for testing of concepts. The opportunity to use path analysis (e.g., structural equation modeling) to test conceptual models is prohibited. The advantage of path analysis is that interrelationships can be identified. Secondly, two measurements were administered over a 10-week time span. Students may be less motivated to fill out the questionnaires. Finally, all measures were self-report measures.

The theoretical model presented in this research was partially confirmed, but future planned studies should also be conducted for different desktop VR systems and increase the sample size to increase the applicability of findings. Since self-efficacy, goal orientation, technology acceptance and learning behavior were found to be subject to change within a short time span, it is necessary for future research to investigate specific methods and pathways to influence these variables and ultimately affect learning behavior in a positive way (i.e., achieve deep learning).

Desktop VR is a practical learning technology that gives students more hands-on opportunities and increases their sense of presence compared to traditional learning; it does not require high equipment costs and does not cause adverse reactions from users compared to immersive VR. Therefore, using desktop VR for learning is a compromise solution. As desktop VR is increasingly used in different teaching and learning areas, its impact on students should also be studied in more depth. Future research ought to consider the role of desktop VR in learning from more perspectives and investigate its impact paths and change paths in greater depth.

Abbreviations

VR	Virtual reality
PEOU	Perceived ease of use
PU	Perceived usefulness
M	Mean
SD	Standard deviation

Acknowledgements
There is no acknowledgment in this study.

Author contributions
All authors were involved in the entire process of experimentation and manuscript preparation. The submitted manuscripts were approved by all authors. All authors read and approved the final manuscript.

Funding
This project has been funded with support from Research on Features and Influence Mechanism of Personalized Learning Behavior Integrating Virtual Simulation Technologies, Philosophical and Social Sciences Project of Shanghai Municipality, 2020 (No. A2006).

Availability of data and materials
The datasets used in the current study can be obtained from the corresponding authors with reasonable requirements.

Declarations

Competing interests
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Received: 7 February 2022 Accepted: 1 June 2022
Published online: 08 June 2022

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