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ORIGINAL ARTICLE

Exploring structural relations among computer self-efficacy, perceived immersion, and intention to use virtual reality training systems

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Abstract
The use of virtual reality (VR) training systems for education has grown in popularity in recent years. Scholars have reported that self-efficacy and interactivity are important predictors of learning outcomes in virtual learning environments, but little empirical research has been conducted to explain how computer self-efficacy (as a subcategory of self-efficacy) and perceived immersion (as a correlate of interactivity) are connected to the intention to use VR training systems. The present study aims to determine which factors significantly influence behavioral intention when students are exposed to VR training systems via an updated technology acceptance frame by incorporating the constructs of computer self-efficacy and perceived immersion simultaneously. We developed a VR training system regarding circuit connection and a reliable and validated instrument including 9 subscales. The sample data were collected from 124 junior middle school students and 210 senior high school students in two schools located in western China. The samples were further processed into a structural equation model with path analysis and cohort analysis. The results showed that the intention to use VR training systems was indirectly influenced by computer self-efficacy but directly influenced by perceived immersion ($\beta = 0.451$). However, perceived immersion seemed to be influenced mostly by learner interaction ($\beta = 0.332$). Among external variables, learner interaction ($\beta = 0.149$) had the largest total effect on use intention, followed by facilitating conditions ($\beta = 0.138$), computer self-efficacy ($\beta = 0.104$), experimental fidelity ($\beta = 0.083$), and subjective norms ($\beta = 0.077$). The moderating roles of gender differences, grade level, and previous experience in structural relations were also identified. The findings of the present study highlight the ways in which factors and associations are considered in the practical development of VR training systems.

Keywords Computer self-efficacy · Perceived immersion · Intention to use · VR training systems · TAM

1 Introduction

1.1 VR training systems in education

The use of virtual reality (VR) training systems for education has grown in popularity in recent years with the increasing recognition of VR features, i.e., immersion, interaction, and imagination (Concannon et al. 2019; Huang et al. 2010). It is broadly accepted that VR offers a very high potential to provide benefits in the context of education by enabling learning to become more motivating and engaging (Freina and Ott 2015). Because such systems exhibit great potential to positively affect learning motivation and attitudes when users are exposed to VR environments (Huang et al. 2016) and strengthen learning outcomes and induce improved knowledge retention (Vaughan et al. 2016), they are widely used in educational scenarios that require reduced risk and are inaccessible in the real world (Pedram et al. 2020). Essentially, the adoption of VR training systems in educational contexts has three purposes. The first purpose is to present the physical positions and geometric structures of objects so that learners can explore the VR learning environment from personalized angles (Jiménez 2019). This process can improve learners' cognition of spatial-related concepts and, more importantly, deepen their understanding of the characteristics, structural principles, and generation of the objects (Bogusevschi et al. 2020). The second purpose is to

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mimic realistic scenes, providing students with an immersive learning experience. Although more realism might not necessarily lead to better learning achievement, it is likely to promote satisfaction, presence, and affective experiences (Makransky et al. 2017). For example, in emergency services simulated by the police force, firefighters, or the army, learners enter into a virtually real scene and interact with graphically generated customers, peers, and computerized tools to motivate their engagement and deeper learning (Lee et al. 2010). Scholars have found that the academic effect of a well-designed and realistic virtual training system is almost the same as the effect of a real-world scene (Bertram et al. 2015). The final purpose for which VR training systems are used is to educate learners in tasks that require fine motor skills, such as driving (Zinzow et al. 2018), dancing, and performing surgery (Pfandler et al. 2017). Training in real situations is very costly and complex, and such training can only include a small variety of real scenarios due to restrictions related to safety and convenience (Concannon et al. 2019). However, VR training systems can provide learners with repeated opportunities to practice, reduce training costs, and improve safety. VR training systems also help students transfer the skills they learn in the virtual environment to practical tasks in reality, thereby allowing them to obtain standard operation specifications and correct conceptual knowledge (Çakiroğlu and Gökoğlub 2019).

However, the fragility, hardware constraints, and potential disorientation and discomfort associated with state-of-the-art VR training systems (Caserman et al. 2021; Krokos and Varshney 2022) have posed great challenges to achieving substantial usage, which has motivated numerous studies in educational science to focus on the usability of VR technology (Abdullah et al. 2016). Few of these studies have focused on student intentions to use these technologies. An individual's intention to use technology can be defined as the degree to which the user would like to use the technology in the future (Joo et al. 2018) and is usually linked to learning preferences, satisfaction, self-efficacy, learning feedback, etc. Students' intention to use technologies provides support for learning environment construction and course design. In some existing studies, scholars have proposed that the intention to use technology is a form of technology acceptance behavior that is relevant to perceived ease of use and perceived usefulness (Lee and Lehto 2013); therefore, the technology acceptance model (TAM) (Davis 1986) can be used to model the relationships among perceived ease of use, perceived usefulness, and the intention to use technology based on the assumption that behavioral intention is a valid predictor of actual use behavior. Sagnier et al. (2020) recognized that the intention to use VR is positively influenced by perceived usefulness but not influenced by perceived ease of use when personal innovativeness and cybersickness are considered in the TAM.

Huang and Liaw (2018) proposed that perceived ease of use, perceived usefulness, and learning motivation are three important factors affecting learners' intention to use VR learning environments when perceived self-efficacy and interaction are incorporated in the model. Fussell (2020) utilized an extended TAM to explain flight students' acceptance of VR for flight training as well as their intent to use the technology; in that study, the original TAM constructs had the strongest relationships, and all other constructs directly or indirectly impacted the intention to use VR systems. Fussell SG and Truong D (2021) added that perceived ease of use and perceived usefulness affected attitudes and behavioral intentions with respect to VR training systems, but performance expectancy and regulatory uncertainty did not exhibit such an effect. In the context of the COVID-19 pandemic, Schiopu et al. (2021) claimed that the intention to use VR was influenced by the perceived ease of use, perceived usefulness, and perceived substitutability of VR, but all of these effects were mediated by user interest. Perceived substitutability is determined by the perceived authenticity of the VR experience. Lin and Yeh (2019) confirmed that interactivity is an attractive option for improving ease of use and usefulness when taking perceived playfulness into account.

1.2 Aim of this study

The studies mentioned above have suggested that when different factors are considered in the TAM, their effects on the intention to use VR systems are not homogeneous. Many of the studies have mentioned the aspects of self-efficacy and interactivity, but little empirical research has explained how computer self-efficacy and perceived immersion are connected to the intention to use VR training systems. Computer self-efficacy, which refers to perceptions of one's ability to perform specific computer-related tasks, has been studied extensively in many non-VR environments as a subcategory of self-efficacy (Hatlevik et al. 2018; Yeşilyurt et al. 2016). Perceived immersion is a correlate of interactivity (Lee et al. 2010) and is usually used to represent the subjective experience of participants who feel as though they are truly in the virtual world, forgetting the real world and losing their sense of time (Shin 2018). It is worth emphasizing that we operationalized perceived immersion only in the form of subjectively experienced immersion and did not refer to technological definitions of immersive types of VR environments following Hudson et al. (2019) and Sutcliffe (2016). In addition, previous studies have explored the effects of individual difference factors such as gender, previous experience, and grade levels on simulator sickness (Grassini and Laumann 2020), learning achievement, and attitudes (Kim 2006). However, little evidence has been provided concerning whether individual difference factors moderate the associations among the determined structural relations. These insights are essential for the development of the VR education environment, the integration of curriculum materials, intervention in the educational process, and our understanding of learners' motivation. Therefore, the main purpose of the present study was to explore the factors that significantly influence use intention as well as the moderating roles of individual difference factors when students are exposed to VR training systems; this objective was pursued by adding the constructs of computer self-efficacy and perceived immersion to an updated TAM.

The contributions of this study can be summarized via the following three aspects.

(1) We developed a reliable and validated instrument for educational scenarios to measure the factors that influence the intention to use VR training systems.
(2) Based on carefully prepared VR course material, we empirically explained the extent to which computer self-efficacy and perceived immersion had an impact on intention to use VR training systems.
(3) We found new evidence concerning the ways in which individual difference factors moderate the structural relations among diverse constructs.

The remaining parts of this paper are organized as follows. Section 2 provides the theoretical basis and research model, Sect. 3 presents the details of methodology, and Sect. 4 reports the results of the study. Conclusions and educational implications are drawn in Sect. 5.

2 Theoretical framework

2.1 Technology acceptance model

Among the various theoretical models related to the acceptance and use of technology, the most popular is the TAM, which is widely used to determine the significant factors contributing to the acceptance of computer technologies or information systems (Lee and Lehto 2013). The original TAM created by Davis (1986) is composed of 5 constructs. Individuals' computer technology use behavior is determined by behavioral intention, while behavioral intention is a function of an individual's attitude toward the behavior and the subjective norms surrounding the behavior (Joo et al. 2018). Individuals' behavioral intention is affected by cognitive beliefs, which account for their overall knowledge and perception of specific computer technologies or information systems (Surendran et al. 2012). Perceived usefulness and perceived ease of use, as the core of the TAM framework, have been generally confirmed to be important measures of an individual's attitude toward both application and tool usage (Venkatesh et al. 2003). Perceived usefulness refers to the degree to which the user believes that using the technology will improve his or her work performance by facilitating the learning process in general and the completion of learning-related tasks in particular (Agudo-Peregrina et al. 2014). Perceived ease of use refers to how effortless he or she perceives use of the technology to be (Huang and Liaw 2018; Surendran et al. 2012), which is typically related to ease of access, navigation, and interface design. In addition, some external variables affect students' attitudes and behavioral intentions by influencing their perceptions of usefulness and ease of use, and user intentions are directly related to learners' usage behaviors (Hsia et al. 2014).

The extended technology acceptance model (TAM2) (Venkatesh 2000; Chang et al. 2017; Sánchez-Prieto et al. 2017) incorporates social factors and cognitive tools into the original TAM and takes into account moderator variables such as voluntariness and previous experience. Beyond the TAM2, the unified theory of acceptance and use of technology (UTAUT) was introduced to explain the extent to which users accept the technology when they are exposed to a specific information system (Venkatesh et al. 2003) by removing the construct of attitude toward use. The UTAUT contains four key components: performance expectancy (perceived usefulness), effort expectancy (perceived ease of use), social factors, and facilitating conditions. The use of moderator variables such as gender, age, previous experience, and participatory voluntariness can further improve the model's interpretability (Chao 2019).

TAM3 is a relatively new theoretical model developed by Venkatesh and Bala (2008). TAM3 includes three extensions and determinants related to social influence processes and an individual's hands-on experience and reflects not only the direct effect of perceived usefulness and perceived ease of use on behavioral intention but also the direct effect of perceived ease of use on perceived usefulness (Lim et al. 2013). TAM3 also specifies cognitive belief as an important construct that influences behavioral intention and that is influenced by individual differences among students, features of the information system, subjective norms, and facilitating conditions (Sagnier et al. 2019). Subjective norms contribute to individual behavioral cognition within social groups, and individual behavioral decisions are often influenced by surrounding social groups. That is, a person who faces social pressure from the opinions of those who are very important to him or her, such as family or friends, will tend to perform a given behavior even if he or she is subjectively unwilling to do so (Agudo-Peregrina et al. 2014). Studies have reported that subjective norms have either a direct or an indirect influence on behavioral intention through perceived usefulness (Abdullah et al. 2016; Chang et al. 2017; Teo et al. 2019). In addition, the facilitating conditions of the TAM3 framework refer to the favorable factors provided by the surrounding environment, such as adequate organizational and technical infrastructure, that support students' completion of specific experimental tasks (Chang et al. 2017). The literature has also widely acknowledged the significant impact of facilitating conditions on behavioral intention. Compared with TAM, TAM2, and UTAUT, the framework presented by TAM3, i.e., external and individual factors, cognitive beliefs, behavioral intention, and actual use behavior (Venkatesh and Bala 2008), provides a more comprehensive and practical model analysis for the present study. Based upon the TAMs and the literature presented above, we propose the following hypotheses like most literature do.

H1 Subjective norms positively influence perceived usefulness.

H2 Facilitating conditions positively influence perceived ease of use.

H3a Perceived ease of use positively influences perceived usefulness.

H3b Perceived ease of use positively influences use intention.

H3c Perceived ease of use positively influences perceived immersion.

H4 Perceived usefulness positively influences use intention.

2.2 Computer self-efficacy

Self-efficacy (Bandura 1977), developed in social cognitive theory, has been documented in different disciplines. It consists of the regulation of cognitive, social, emotional, and behavioral skills required to perform a task (Yeşilyurt et al. 2016). A large body of studies has reported that self-efficacy has a positive and significant relationship with academic achievement (Öztürk and Şahin 2015). Computer self-efficacy is typically regarded as one aspect of self-efficacy that explains individuals' beliefs regarding their ability to solve tasks when using specific computer technologies (Compeau and Higgins 1995). Because of the high technical threshold for students, computer self-efficacy is an important factor that affects their use of VR training systems. Given similar cognitive and skill levels, students with high computer self-efficacy tend to spend more time using computer-related technology than students with low computer self-efficacy and are therefore more engaged in the learning processes (Bates and Khasawneh 2007; Awofala et al. 2019). Students who have negative perceptions of their ability to perform computer-related tasks successfully are less likely to use computer systems, and by contrast, students with high computer self-efficacy are more willing to learn by using the computer (Mcilroy et al. 2007; Srisupawong et al. 2018). Scholars have identified numerous behavioral, cognitive, attitudinal, and environmental influences on computer self-efficacy and suggested that computer self-efficacy is significantly correlated with computer anxiety, which is defined as fears pertaining to the implications of computer use, such as the loss of important data or other possible mistakes (Awofala et al. 2019; Celik and Yesilyurt 2013; Laily and Riadani 2019; Marakas et al. 1998). That is, individuals with high computer self-efficacy might be expected to perceive themselves as able to accomplish more difficult computing tasks than those with lower computer self-efficacy (Compeau and Higgins 1995). As technologies are incorporated into education, a rich body of studies has focused on computer self-efficacy because computers are a basic tool that supports the learning process (Scherer and Siddiq 2015). The early nonexperimental and experimental research reviewed by Moos and Azevedo (2009) suggested that both psychological and behavioral factors, e.g., a positive attitude, curiosity, and intrinsic motivation regarding computer systems, are related to computer self-efficacy, which influences learning outcomes and learning processes. Computer self-efficacy has been recognized by some later studies (Hsia et al. 2014; Laily and Riadani 2019; Teo and Zhou 2014) as an important determinant of perceived ease of use and to have significant effects on the intention to use computer technology (Chow et al. 2013; Hsia et al. 2014; Li et al. 2019; Turan and Cetintas 2020). Student beliefs, as a key aspect of computer self-efficacy, affect their attention, engagement, and effort with respect to completing computer tasks successfully and further influence students' acceptance of new information technologies, motivation, and even success in electronic courses (Srisupawong et al. 2018). Nevertheless, some studies have indicated that computer self-efficacy has little association with behavioral, emotional, and cognitive engagement when situational interest and self-regulation are considered in the model (Sun and Rueda 2012). In view of these studies, we propose the following hypothesis.

H5 Computer self-efficacy positively influences perceived ease of use.

2.3 Perceived immersion

Perceived immersion has been identified as a psychological state that is characterized by perceiving oneself to be enveloped by, included in, and engaged in interaction with an environment that provides a continuous stream of stimuli and experiences (Witmer and Singer 1998). Relationships among perceived immersion, perceived usefulness, and behaviors in VR learning environments have been documented in recent decades. Huang et al. (2010) identified that students' perceived immersion in desktop-based VR could positively predict their motivation, problem-solving capability, collaborative learning, and behavioral intention to use VR systems. Huang et al. (2020) further studied the impacts of perceived immersion and sensory fidelity on affective learning outcomes. A well-designed VR environment with a higher degree of sensory fidelity is able to create a deep level of perceived immersion, which produces more believability for the user and has stronger effects (Al-Jundi and Tanbour 2022). Cheng and Tsai (2020) subdivided perceived immersion into the elements of basic attention, temporal dissociation, transportation, emotional involvement, and enjoyment and noted that students' immersive experiences of attention and enjoyment significantly mediated their VR-based learning. Perceived immersion has been examined and understood as a positive affective dimension pertaining to interactive media use, through which participants can experience a modified sense of time and decreased self-consciousness. Thus, perceived immersion is commonly linked to satisfaction and loyalty in the context of VR experience (Hudson et al. 2019). Lange D et al. (2020) connected directional cues to immersive experience in a VR environment and proposed an attention guidance technique to preserve the perceived immersion of users. Makransky and Lilleholt (2018) proposed that students' perceptions of being immersed in immersive VR could be strongly related to their sense of presence, positive emotions, and cognitive value. Presence and perceived immersion are often used synonymously, but they actually refer to distinct concepts. Presence represents a mental state in which users recall VR experiences as if they had actually occurred by providing a sense of embodied cognition (Al-Jundi and Tanbour 2022). This trait helps participants create a sense of "being there" by means of tangible interactions within the VR environment. Perceived immersion is defined as a subjective experience that is characterized by deep physical and mental involvement, which causes participants to lose track of time and forget certain unrelated events (Wang et al. 2017). In this sense, perceived immersion has a broader definition than presence in that the former allows users to encounter a perceptual illusion of unmediated experience in a setting mediated by technology (Hudson et al. 2019). According to McMahan (2013), presence is the result of perceived immersion by blocking as many senses focusing on the outside world as possible and making it possible for participants to perceive the artificial world. Accordingly, the level of subjectively engrossing experience predicts sensory fidelity and usability, which in turn predict affect, cognition, and perceived learning outcomes. Chu et al. (2019) found that students with low academic competence expressed stronger feelings of attention attraction and enjoyment than those with high academic competence. In short, existing works have confirmed that perceived immersion has multiple positive impacts on learning performance. Little is known regarding how perceived immersion influences the intention to use VR training systems when multiple constructs, such as a combination of perceived usefulness, perceived ease of use, subjective norms, facilitating conditions, and computer self-efficacy, are incorporated into the research framework. Therefore, we propose the following hypothesis.

H6 Perceived immersion positively influences intention to use.

2.4 Experimental fidelity and learner interaction

According to Lee et al. (2010), the VR environment features representational fidelity and immediacy of control, which are directly and indirectly linked to a number of noncognitive outcomes, including motivation, presence, and usability. Usability specifically characterized as perceived usefulness and perceived ease of use is a measure of basic technology acceptance (Makransky and Lilleholt 2018). The representational fidelity studied by Choi and Baek (2011) refers to features of the realistic display of the environment and the smooth display of changes in view and object motion. The immediacy of control, also labeled interactivity, affects engagement and the experience of flow in VR learning environments (Dalgarno and Lee 2010). Merchant et al. (2012) confirmed that representational fidelity and learners' interaction were two important characteristics of the VR environment. The present study follows their point of view and emphasizes experimental fidelity and learner interaction as features of a VR training system. Experimental fidelity refers to the degree of realism offered by the experimental scene and the objects inside the scene, such as a realistic environment display, spatial audio, movements, and tactile feedback. We thus propose the following two hypotheses.

H7a Experimental fidelity positively influences perceived usefulness.

H7b Experimental fidelity positively influences perceived immersion.

In the present study, learner interaction (Dalgarno and Lee 2010) focuses on the interaction between the learner and the interface of VR training systems, such as view control, navigation, and object manipulation, although the conception of interaction has been extended from interaction between the student and the environment to encompass social interactions among students. We thus propose the following hypotheses.

H8a Learner interaction positively influences perceived ease of use.

H8b Learner interaction positively influences perceived immersion.

2.5 Individual difference factors

Educational studies have identified a wide spectrum of individual difference factors, including gender, previous experience, and grade level (Wahyudiati et al. 2020). However, the moderating roles of such individual differences have not been widely studied in VR. In previous studies, females have commonly been reported to be more sensitive to simulator sickness in VR (Munafo et al. 2017) and less likely to repeat the simulation experience (Rangelova and Marsden 2018). Howard et al. (2021) emphasized that VR sickness produced unequal effects across gender differences. Students with different gender had different gaze sequences and male students showed longer fixation durations than female students (Hung and Wang 2021). Lin and Yeh (2019) identified that perceived ease of use was a major contributor to the intention to use VR systems and found no gender differences, but the effect of perceived usefulness on the intention to use VR systems was observed only in the case of females. However, little evidence has shown how gender differences influence structural relations among perceived usefulness, perceived ease of use, perceived immersion, etc. A recent study reported that gender differences moderated the relationships among perceived usefulness, intention to use, and learning performance (Wongwatkit et al. 2020). Therefore, we propose the following hypothesis.

H9a Gender differences moderates structural relations.

In addition, previous experience with VR serves as a reference point for the mental representation of the VR environment. Scholars have reported that previous experience affects the sense of spatial presence and attitude (Sagnier et al. 2019) and moderates the relationship between satisfaction and continuance intention (Lin 2011). We thus posit the following hypothesis.

H9b Previous experience moderates structural relations.

In addition, the grade levels of students represent distinct contexts with unique characteristics derived from the underlying grade climate. As a proxy for age, the grade level has been reported to moderate the associations among perceived ease of use, perceived usefulness, and behavioral intention (Tarhini et al. 2014). We therefore propose the following hypothesis.

H9c Grade level moderates the structural relations.

3 Research model

Based on the TAM3, all the variables in the present study are adjusted in accordance with four categories: external variables correspond to computer efficacy, experimental fidelity, learner interaction, subjective norms, and facilitating conditions; moderator variables include gender, previous experience, and grade level, which can moderate the relationships among the variables included in the TAM; the outcome variable, corresponding to the dependent variable in this study, refers to students' behavioral intention to use VR training systems and measures the extent to which they are willing to use these systems; and the mediator variables focus on the constructs of perceived usefulness and perceived ease of use in the original TAM3 with the addition of the perceived immersion construct at the level of cognitive beliefs, indicating that the interaction between the individual and the computer is affected by the environment surrounding the individual. The research model used in this study is illustrated in Fig. 1.

4 Methodology

4.1 Research context

The country has recently encountered unprecedented educational innovations driven by new-generation information technologies. VR technology has been promoted vigorously by most policy-makers and scholars. However, although many schools have purchased a great deal of hardware equipment, they lack the corresponding curriculum resources, indicating that the actual teaching application of this technology remains at an early stage of development. To understand which factor affects students' intention to use VR training systems in light of the possibility that virtual training can replace certain aspects of real tasks in the future, we developed a series of VR training systems related to engineering technology with the goal of training students' operational skills. These systems refer to a diverse range of themes, including circuit connection, computer assembly, and mechanics. Because students at different levels have different cognitive levels with respect to the same theme, we ultimately decided to choose one of these training systems, entitled *Exploring the Relationship between Currents in Series Circuit*, as the experimental scenario; this training corresponds to one chapter of physics textbooks at the junior middle school level. This scenario is well known to both junior middle school and senior high school students,

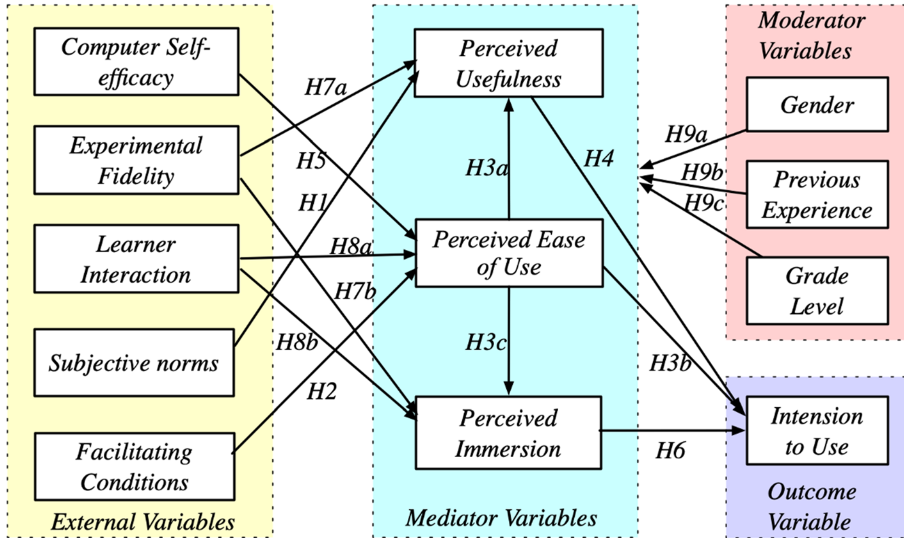

Fig. 1 Research model

which can reduce the influence of scenario familiarity and cognition diversity on VR operation. Students were expected to use VR hardware devices to connect the ammeter, light bulbs, batteries, switches, and wires correctly and to record corresponding readings on the ammeter by selecting digits on a virtual panel once the light bulbs were successfully lit.

4.2 Development of the VR training system

4.2.1 Configurations and settings

The hardware used for debugging during the development stage was a group of HTC VIVE Kits. Each group kit included a high-performance computer with a high-definition screen, a wired head-mounted display (HMD) with a resolution of 2160*1200, two handle controllers, and a pair of laser positioners. Considering the fact that different schools might have different versions of this hardware, we configured the system to be compatible with VIVE Pro 2 at a resolution of 4896*2448. Accordingly, in the experimentation stage, we used the same hardware devices as those used in the development stage. The VR software system was developed using the VR editing software VeryEngine (https://veryengine.com/). VeryEngine, which is based on the popular game engine Unity 3D, is a rapid VR development platform designed specifically for training institutions and schools. It provides flexible Microsoft Excel-style functions to allow anyone who has few programming skills (e.g., science teachers in primary schools) able to create and edit VR education resources and virtual environments conveniently. Because this software has low technical requirements and is available on both Android and web platforms, teachers in training institutions and schools are able to produce high-quality VR education resources at any place and any time, promoting practical VR teaching applications instead of requiring them to stay in the laboratory.

The development framework for the VR training system is illustrated in Fig. 2. We used Excel sheets to edit the parameters of virtual objects and to define interactive behaviors between human and virtual objects. These Excel sheets were connected to the C# programming language via the Unity 3D game engine to offer extended functions so that the system can meet any necessary requirements for educational software. We provided roaming, collision, ray selection operations, and standard laboratory configurations similar to those found in the real world (e.g., whiteboards, tables, chairs, instrument storage cabinets) to reduce unfamiliarity and computer anxiety. The visual models of the virtual laboratory apparatus were created in 3D Max software in compliance with the recommendations of the latest course standards in China. We created a virtual keyboard panel for learners to record experimental data and to enable the production of learning profiles for download after participants completed the experiment. Multimodal feedback (i.e., feedback in the form of visuals, voice, text, and emojis) was incorporated into the virtual scene to help participants receive timely sensory stimulation. It is widely accepted that the quality of learning environments affects students' knowledge construction process (Yerdelen and Sungur 2019). Participants in this study were incited in world to complete the experiment through self-regulation which is an effective knowledge construction approach embodied in the constructivism theoretical framework. Constructivism is typically evaluated as a process relying on students' autonomy and self-awareness (Pande and Bharathi 2020); self-regulation in the current study entails an active and constructive process whereby participants are able to regulate their behaviors by the constraints of predetermined circuit connection tasks and the contextual features of the VR training system. As

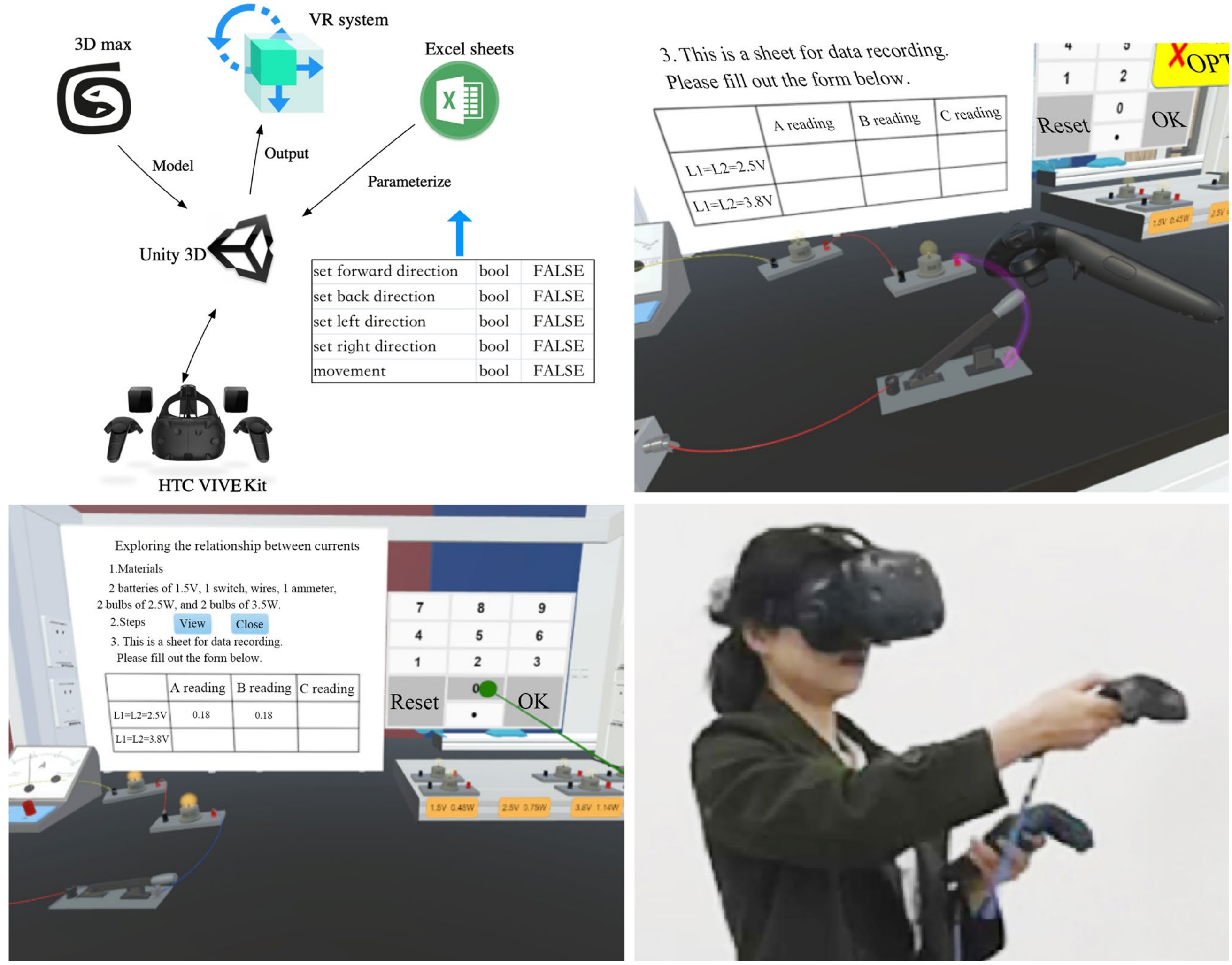

Fig. 2 The VR training system developed for educational purposes. Excel sheets were combined with 3D Max and Unity 3D software for the creation and editing of VR education resources and interactions. Students use an HMD and handle controllers to connect circuits correctly and record readings on an ammeter via a virtual digital panel

a result, the developed VR training system based on constructivism allows participants to acquire new reasoning and operational skills by combining their previous learning experiences in the physical world with their newly established mental processes. Nisha (2019) has confirmed that self-regulated learning in such a VR system is significantly effective in terms of enhanced learner engagement and learning gain in the process of knowledge construction.

4.2.2 Iterations for educational purposes

Because the system was designed for educational purposes, we conducted careful preparation before experimentation to make the system more functional and usable. To this end, the system was optimized iteratively over the course of half a year in accordance with a design-based research method (Zydney et al. 2020) (an approach that is well known in education research due to its formative evaluation of newly established educational environments, software tools, and subfunctions; the system underwent two rounds of evaluation and a system revision following each round), in which context we highlighted the aspects of perceived immersion and emotional support because they were considered to be significantly related to the current study. We used a popular emotional design model (i.e., Donald Norman's emotional design model (Norman 2007)), which is based on cognitive science and product design principles. The division of emotion into visceral, behavioral, and reflective layers corresponded to the three-level information processing that is performed by the human brain, i.e., focusing on affective, cognitive, and reflective aspects (Panksepp et al. 2017). The visceral layer mainly considered esthetic aspects of the system and was used to influence human biological responses and to demand a rapid judgment concerning the appearance of the system. The behavioral layer mainly focused on physical perceptions of the usability, effectiveness, and ease of use of the system. The reflective layer highlighted high-level cognitive processing, such as satisfaction, accomplishment, and related memories, accounting for participants' ability to maintain an innate sense of identity. The final VR system was confirmed to have significant positive effects on participants' immersive experiences (the procedure and statistics are not reported here because they are not within the scope of the current study), which motivated us to use this system to investigate structural relations among multidimensional constructs in this study. Part of the iteration process for the system is presented in Table 1.

4.3 Sampling

This study obtained data from two middle schools in western China. To obtain quality data and a sufficient sample size, some scholars have suggested ways of determining representative samples and their quantity. One general rule is that sample sizes below 100, between 100 and 200, and over 200 are often considered to be small, medium, and large samples, respectively (Kline 2015). Tabachnick et al. (2007) suggested adopting the equation $N > 50 + 8M$ to determine the quantity, where M is the number of independent variables and N is the number of samples. Breckler and Berman (1991) posited that study results can be stable only when the sample size is greater than 200. In this study, we recruited participants who had studied the *Exploring the Relationship between Currents in Series Circuit* chapter and obtained a total of 402 initial samples. After removing 58 invalid samples (i.e., samples that missed answers or overstated answers), 334 valid samples were eventually obtained, with an effective rate of 83.08%, which met the requirement of the minimum sample size.

The demographic statistics for the final samples were as follows: 38% ($N = 127$) of participants were male, and 62% ($N = 207$) were female. A total of 37.1% ($N = 124$) of participants were in junior middle school, and 62.9% ($N = 210$) were in senior high school. Students' ages were consistent with their grade levels (i.e., junior middle school students were younger and senior high school students were older). Thus, we did not include age as a variable. In this investigation, the notion of VR systems included both desktop-based virtual systems and head-mounted displays. A total of 38.9% ($N = 130$) of participants reported that they had no VR experience, 49.1% ($N = 164$) reported that they had entry-level VR experience, and the remainder reported that they were very familiar with VR ($N = 40$). Most students reported that they had used desktop-based virtual systems, and a few participants ($N = 13$) had used head-mounted displays. Since there were very few participants who were familiar with VR, we combined that type of student and those who were

Table 1 Iterations of the system

Dimension	First-round iteration	Second-round iteration
Visceral Layer	Create tables, ammeters, light bulbs, batteries, switches, and wire models similar to those in a real laboratory	Improve the reality of the models. Modify the "wire" function so that the connected nodes are highlighted in red. When the learner makes a mistake, the system prompts the learner with voice instead of text
Behavioral Layer	Participants use handles to "pick up", "roam", "place", and "drop" items, etc., with improved measures of "easiness-to-use" and "sensitivity"	Reduce the difficulty of circuit connection. The distance between end points within a predefined value is connected automatically. Reduce the number of false touch operations such as "multiple selection" and "wrong selection"
Reflective Layer	When connected correctly, the light bulbs glow and the readings of the ammeters change; when the learner fails to connect, the system provides textual feedback	When the learner takes no action in the experiment for more than 3 min, the system prompts the learner to proceed to the next operation; when the learner makes 3 consecutive errors, the system explains the error and then shows the correct operation to the learner. When the learner succeeds, the system displays an animated prompt such as "Awesome" or "Great"

initially exposed to VR into one group to make the data more balanced.

4.4 Instrumentation

The instrument developed in the present study was a self-report questionnaire called the Intention to Use VR Training Systems (IUVRTS) that aimed to assess the factors that influence participants' intention to use VR training systems. The first part of the questionnaire obtained demographic data from the subjects, including gender, grade level, and previous experience with VR, and these data were used as moderator variables in this study. The second part pertained to the variables hypothesized in the research model and formed 9 subscales. To meet the requirements of structural equation modeling, each latent variable was designed to contain at least 3 items, and each item was quantified on a Likert scale ranging from 1 to 5: completely disagree, disagree, uncertain, agree, and completely agree. The instrument contained a total of 34 measurements.

The *computer self-efficacy* (CSE) subscale contained 4 items to measure individuals' beliefs regarding their ability to solve tasks when using VR training systems. According to a review of computer self-efficacy measurements conducted by Compeau and Higgins (1995), existing measures used 3-, 4-, or 5-item scales, but did not assess the perception of one's ability to carry out specific tasks. The computer self-efficacy subscale employed the magnitude and strength dimensions of computer self-efficacy measures suggested by Compeau and Higgins (1995) and Turan and Cetintas (2020) and obtained an α value of 0.838.

The *experiment fidelity* (EF) subscale derived from the work of Dalgarno and Lee (2010) and Merchant et al. (2012) contained 4 items pertaining to the realistic display of the environment and the consistency of object behavior. We obtained an α value of 0.873 for this subscale.

The *learner interaction* (LI) subscale contained 4 items, and an α value of 0.873 was obtained for this subscale. This subscale measured the controllability of VR instruments (Merchant et al. 2012).

The *subjective norm* (SN) subscale contained 3 items, and the *facilitating conditions* (FC) subscale contained 5 items; both of these subscales were derived from the work of Venkatesh and Bala (2008). The α value for the subjective norm subscale was 0.800, and the α value for the facilitating conditions subscale was 0.867.

The *perceived usefulness* (PU) subscale and *perceived ease of use* (PEOU) subscale were the main constructs of the TAM according to Venkatesh and Bala (2008). These subscales included 4 and 3 items and scored α values of 0.889 and 0.817, respectively.

The *perceived immersion* (PI) subscale contained 4 items and was derived from the Immersive Experiences Questionnaire (IEQ) developed by Jennett et al. (2008). According to the IEQ and Cheng and Tsai (2020), measurements of perceived immersion include basic attention (the extent to which users feel that they are focused on virtual environments), temporal dissociation (the extent to which users perceive themselves as losing track of time), enjoyment (the extent to which users feel enjoyment when performing the task), and transportation (the extent to which users have a stronger awareness of being in the virtual environment than in the real world). The α value for this subscale was 0.855.

The *behavior intentio*n (BI) subscale contained 3 items to measure students' subjective probability of using a VR training system. According to Venkatesh and Bala (2008), behavioral intention is a major determinant of actual usage behavior. The α value for this subscale was 0.827.

The instrument items are described in the Appendix. The Cronbach's α for each subscale was higher than 0.8, and the removal of any item from the scale did not significantly improve its reliability. The overall Cronbach's α for this instrument was 0.941. Because Cronbach's α reflects the degree to which items on the scale are interrelated but does not necessarily provide information concerning the unidimensionality of the construct (Schmitt 1996), we also calculated the corrected item-total correction (CITC > 0.5). Together, Cronbach's α and CITC indicated that the reliability of the instrument was excellent. In addition, the Bartlett test (approximate $\chi 2 = 2435.600$, df = 561, $p < 0.001$) suggested that the sample can be processed via factor analysis. After 7 iterations, a total of 9 factors were extracted, and the cumulative explanatory variation was 73.14%. The extracted factors were perfectly consistent with the hypothesized 9 variables, indicating that the sample exhibited good validity.

4.5 Procedure

At the initial stage, we conducted a pretest of the scale by selecting students from the same schools. A total of 130 questionnaires were administered, and the total usable sample was 107 (84.92%). We encouraged students to provide feedback regarding the instrument, and overall, they indicated that the questionnaire was clear and easy to complete.

To evaluate item fitness, item analysis was performed on the pretest sample to determine whether the various items could effectively identify the grade levels of the subjects. We calculated the total score for each sample and ranked them in ascending order; subsequently, we grouped the top 27% and the bottom 27% into high-scoring and low-scoring groups, respectively. The low-scoring group was named Group 1, and the high-scoring group was called Group 2. Then, we conducted an independent-sample T test on the groups, which showed that the critical value for the top 27% of the sample corresponded to the score for the 29th percentile and that the critical value for the bottom 27% of the sample corresponded to the score for the 79th percentile. The determinate values of items in the pretest sample were significant ($p < 0.001$). Therefore, these 34 items were retained for formal experimentation.

To complete the experiment in the sampled schools successfully, teachers of information technology courses in both schools agreed to guide the experiment. These teachers were first trained to use VR training systems adeptly and were then encouraged to express any concerns or possible problems during the experiment, including issues with network bandwidth or latent technical failures. We addressed these concerns in detail and provided a manual in case the teachers perceived the problems to be obstacles to the experiment. Before the first use of the VR training system, students were required to report their level of previous VR experience. Students who had VR experience were required to use the VR training system independently, and students without VR experience were trained prior to the experiment to familiarize them with virtual scenes and allow them to acquire the necessary operational skills. Teachers guided students to explore the VR training system for at most 15 min per student and addressed technical problems if students were not active throughout the whole usage process. The experiment was conducted outside of the course and lasted for one month in total. When the experiment was completed, students were asked to complete the IUVRTS questionnaire.

4.6 Data analysis

This study used AMOS 24.0 software for structured equation modeling to examine the relationships among the constructs within the proposed model. To verify the reliability and validity of the model, we first conducted confirmatory factor analysis (CFA) to examine whether the observed variable could be used as an effective indicator of the latent variable, and maximum likelihood estimation was used to estimate the model's parameters based on variance–covariance matrices. We used item reliability, convergent validity, and discriminant validity to evaluate the measurement model. The reliability of an item was assessed by its factor loading onto the underlying construct; according to Hair (2009), this value should be between 0.5 and 0.95. Convergent validity refers to the degree to which two measures of constructs that should theoretically be related are in fact related. Convergent validity can be assessed through the composite reliability of each construct and the average variance extracted (AVE) (Fornell and Larcker 1981). Composite reliability requires a value of 0.7 or higher, and the AVE should be greater than 0.5. Discriminant validity pertains to the degree to which two conceptually similar concepts are distinct. The intercorrelation among variables should be smaller than the square root of the AVE (Bagozzi 1981).

After revising the model according to the match between the initial model and the actual sample, we performed path analysis and cohort analysis. At the stage of path analysis, we adopted Chi-square fit statistics/degree of freedom (CMIN/DF), root-mean-square error of approximation (RMSEA), root-mean-square residual (RMR), goodness-of-fit index (GFI), comparative fit index (CFI), incremental fit index (IFI), and parsimony-adjusted normed fit index (PNFI) to evaluate the established paths. At the stage of cohort analysis, we adopted the critical ratios (i.e., Z score) for differences between the parameters to examine whether the variables (gender, learning stage, and experience) at different levels had a moderating effect on the corresponding path. A critical ratio greater than 1.96 ($p < 0.05$) means that the moderator variable has a significant impact on the path.

5 Results

5.1 Descriptive statistics

The descriptive statistics for the 9 constructs and corresponding items are shown in Table 2. All the means of the constructs were greater than 3.0, ranging from 3.81 to 4.36. This result indicates that students generally responded positively to the constructs. Students scored highest on experimental fidelity and learner interaction, indicating that the VR training system exhibited excellent VR-related features. The standard deviations of the constructs were less than one, indicating that the respondent scores were relatively close to the mean scores.

5.2 Measurement model

CFA showed that the item reliability ranged from 0.619 to 0.864, and most values were larger than 0.7. The minimum AVE for each construct was 0.566, higher than the suggested value of 0.5. The values on the main diagonal (square roots of the AVE) were all above the inter-construct correlation

Table 2 Descriptive statistics

Subscale	N	Mean	Std	S.E
CSE	334	3.97	0.77	0.042
EF		4.35	0.76	0.042
LI		4.36	0.75	0.041
SN		4.12	0.65	0.036
FC		4.25	0.77	0.042
PU		4.14	0.80	0.044
PEOU		3.81	0.77	0.042
PI		4.11	0.78	0.043
BI		4.14	0.71	0.039

coefficients shown in Table 3. In sum, the measurement model satisfied all three necessary criteria, indicating that the items in each construct were reliable, highly correlated, and distinct from each other.

In the hypothetical starting model, the GFI (0.827), CFI (0.898), and IFI (0.898) did not achieve the required level, and we considered re-specifying the measurement model. With reference to modification indexes (MIs), we considered adding paths and then removing paths in accordance with the work of Bedford (2005). Because the MI between e9 and e12 was the largest (25.66) and because both were closely related to the variable learner interaction, we considered increasing the path between e9 and e12. The fit indexes of the adjusted model were as follows: CMIN/DF = 2.263, RMSEA = 0.062, RMR = 0.061, GFI = 0.830, CFI0 = 0.903, FI = 0.902, and PNFI = 0.753. All the indexes aside from the GFI illustrated that the model fit was better than that of the starting model. Therefore, we developed the full structural equation model illustrated in Fig. 3.

5.3 Structural relations

The final standardized path coefficients based on the structural equation model are established in Fig. 4. The results do not support H7b, H8a, and H3b ($p > 0.5$). H7a is supported at a significance level of 0.05 ($p = 0.026$), and H1, H2, H3a, H3c, H4, H5, H6, and H8b are supported at a significance level of 0.001.

Many relationships among the measured variables were confirmed and exhibit consistency with most of the relevant literature. That is, facilitating conditions significantly influenced perceived ease of use, subjective norms significantly influenced perceived usefulness, perceived usefulness significantly influenced the intention to use VR training systems, and perceived ease of use significantly influenced perceived usefulness.

A new discovery of this study was that the relationship between perceived immersion and the intention to use VR training systems appeared to be the strongest among all the established paths. Moreover, the relationship between perceived ease of use and perceived immersion appeared stronger than that between computer self-efficacy and perceived ease of use. In addition, the relationship between learning interaction and perceived immersion appeared to be stronger than the relationship between experimental fidelity and perceived usefulness.

The effects of the variables on the intention to use VR training systems included both their direct and indirect effects. Among mediator variables, perceived immersion ($\beta = 0.451$) had the largest total effect on the intention to use VR training systems, followed by perceived ease of use ($\beta = 0.248$) and perceived usefulness ($\beta = 0.121$). Among external variables, learner interaction ($\beta = 0.149$) had the largest total effect on the intention to use VR training systems, followed by facilitating conditions ($\beta = 0.138$), computer self-efficacy ($\beta = 0.104$), experimental fidelity ($\beta = 0.083$), and subjective norms ($\beta = 0.077$).

The impacts of the moderator variables are provided in Table 4. Grade level (i.e., junior middle/senior high school students) moderated both the influence of computer self-efficacy on perceived usefulness and that of perceived ease of use on perceived usefulness. Previous experience significantly affected the path of computer self-efficacy to perceived ease of use, the path of experimental fidelity to perceived usefulness, the path of subjective norms to perceived usefulness, and the path of perceived usefulness to behavioral intention. Significant gender differences were observed in the paths from learner interaction to perceived immersion and from perceived immersion to behavioral intention.

In summary, complete paths can be traced in the model. Such paths include CSE → PEOU → PU → BI, EF → PU → BI, LI → PI → BI, SN → PU → BI, FC → PEOU → PU → BI, PEOU → PU → BI, and PEOU → PI → BI. Most paths can be moderated by one or a combination of the factors of previous experience, grade level, and gender.

Table 3 Inter-construct correlation and square roots of AVE

	CSE	EF	LI	SN	FC	PU	PEOU	PI	BI
CSE	**0.752**								
EF	0.408	**0.797**							
LI	0.478	0.628	**0.793**						
SN	0.283	0.541	0.452	**0.762**					
FC	0.428	0.518	0.614	0.519	**0.760**				
PU	0.323	0.415	0.458	0.500	0.612	**0.834**			
PEOU	0.446	0.463	0.356	0.536	0.454	0.454	**0.769**		
PI	0.341	0.437	0.503	0.506	0.561	0.575	0.504	**0.766**	
BI	0.460	0.565	0.510	0.493	0.571	0.521	0.426	0.613	**0.786**

Bold values indicate the square roots of the AVE values

Fig. 3 Measurement model

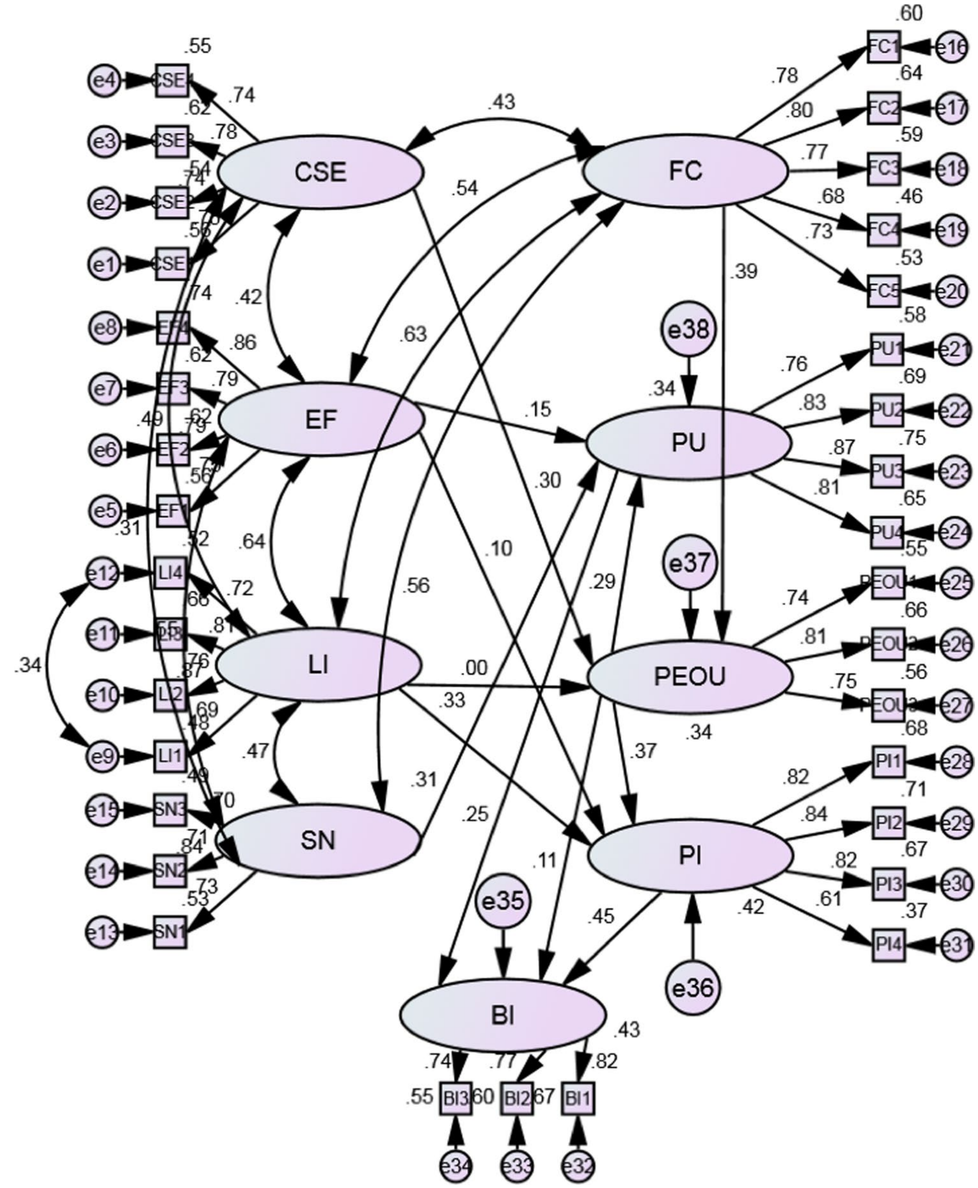

Fig. 4 Structural path coefficients among the measured constructs

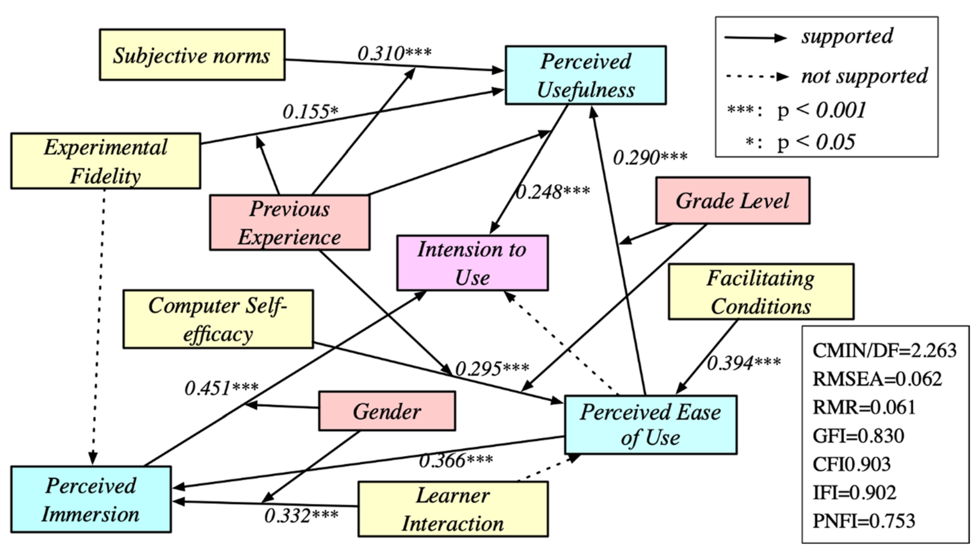

Table 4 Impact of mediator variables

Hypothesis	Path	Gender		Gender		Previous experience	
		Z score	Supported?	Z score	Supported?	Z score	Supported?
H9a-H9c	CSE→PEOU	− 1.080	×	− 3.100		− 2.114	
	EF→PU	1.585	×	1.266	×	2.637	
	LI→PI	− 2.450		− 0.873	×	− 0.438	×
	SN→PU	− 0.864	×	− 1.291	×	− 3.561	
	PU→BI	− 0.127	×	− 1.113	×	− 2.031	
	PEOU→PU	− 1.569	×	− 2.291		1.571	×
	PEOU→PI	1.358	×	− 0.106	×	0.391	×
	PI→BI	3.436		0.487	×	1.383	×

6 Conclusion and discussion

This study explored the relationships among computer self-efficacy, perceived immersion, and intention to use VR training systems via an updated TAM3 framework. For that purpose, we developed a reliable and validated IUVRTS instrument featuring 9 subscales. The CFA results showed that the measurement model fit the data well with respect to evaluations of reliability, convergent validity, and discriminant validity. Therefore, we proceeded with path analysis and cohort analysis. Overall, we found empirical evidence for most of the assumptions made by the relevant literature. Some of our findings were consistent with the literature, e.g., the significant influences of subjective norms and facilitating conditions, while others were newly identified, e.g., the significant influences of computer self-efficacy and experimental fidelity as well as the moderating roles of gender and previous experience on the patterns identified. Based on these study findings, we can draw three important conclusions.

First, facilitating conditions and subjective norms are important constructs that predict the intention to use VR training systems through the mediation of either perceived usefulness or perceived ease of use. Student perceptions of the usefulness of VR training systems seem to influence students' intention to use those systems directly, and perceived ease of use seems to influence such use intention indirectly via perceived usefulness and perceived immersion. It is easy to infer that positive evaluations from people around such students can help them make positive decisions, whereas negative evaluations from those around them may have a negative impact on students' intention to use these systems. This conclusion with regard to subjective norms is in perfect agreement with the claims of Chang et al. (2017) and Teo et al. (2019), but the association does not seem to be independent. The present study revealed the following interesting dependency. Previous experience appears to moderate the associations between subjective norms and perceived usefulness significantly. For students with advanced VR experience, we observed strong correlations between subjective norms and perceived usefulness. However, none of the moderating variables (i.e., previous experience, grade level, and gender) plays a moderating role in the associations between facilitating conditions and perceived ease of use. Perceived ease of use influences both perceived usefulness and perceived immersion directly such that it can indirectly predict use intention, which is moderated by various combinations of previous experience, grade level, and gender.

Second, the present study reveals that computer self-efficacy tends to have direct and positive influences on perceived ease of use but merely indirect influences on the intention to use VR training systems. Previous experience seems to moderate the extent to which computer self-efficacy influences perceived ease of use. That is, students who have had advanced experience with VR tend to use the system more intentionally, whereas students who are new to the system tend not to use it if no proper incentives are provided. This is because more experienced students are more confident in their computer skills and are consequently more inclined to consider VR experiments to be easy to complete. In addition, different grade levels moderate the impact of computer self-efficacy in both direct and indirect ways. Junior middle school students' perceived ease of use seems to be more affected by computer self-efficacy and perceived usefulness. This trend can be explained in two ways. On the one hand, junior middle school students are believed to be less independent than senior high school students (Liu and Fraser 2013). The lower students' grade level is, the less likely they are to be self-regulated; thus, according to Lin and Lai (2019), the effect of perceived ease of use or effort expectation is significantly larger among higher-grade students than among lower-grade students. On the other hand, many scholars have repeatedly claimed that computer self-efficacy is negatively related to computer anxiety, which refers to a feeling of apprehension or anxiety with respect to computer use (Awofala et al. 2019; He and Freeman 2010). Computer anxiety is a term used in psychology to indicate emotional arousal that is caused partly by fear of impending stress in which students doubt their ability to perform the target behavior (Eryilmaz and Cigdemoglu 2019). Therefore, reducing the technical usage concerns of junior middle school students can improve their computer self-efficacy and perceived ease of use and ultimately increase their intention to use VR training systems.

Third, experimental fidelity seems to have a direct influence on perceived usefulness but not on perceived immersion. Experimental fidelity can influence the intention to use VR systems through perceived usefulness; however, this association may be moderated by the previous experience of students. In other words, experienced students may be more concerned about the realism of the VR experimental environment and the provisions of useful tools and functions; however, students who are new to the system may be more concerned about the level of effort they should exert. Notably, higher experimental fidelity, as measured in the present study, does not necessarily lead to improved perceived immersion. This finding does not support the claim that the degree of realism of the objects and situations in the environment is linked with students' immersive experience (Choi and Baek 2011). Nonetheless, higher experimental fidelity is more likely to create opportunities for students to experience the available virtual tools and functions of the systems, according to Pedram et al. (2020). Additionally, our findings reveal that learner interaction has a positive influence on perceived immersion but no effect on perceived ease of use. This finding supports flow theory, and it has been empirically confirmed by many studies that greater interaction might not necessarily be related to better perceived ease of use, although it is likely to enhance users' enjoyment of the experience, according to a meta-analysis conducted by Rahmi et al. (2018). In this way, students concentrate more on their activity and lose track of time (Csikszentmihalyi 2014). Among all external variables, learner interaction appears to have the strongest total influence on use intention, but this association may vary due to both the mediation of perceived immersion and the moderation of gender differences. Hence, we suggest that the nature of learner interaction in designing VR training systems should be given more attention than experimental fidelity.

Overall, the methodology presented in this study seems promising for investigating student perceptions of VR training systems. The strength of the relationships included in the measurement model indicates the constructs and associations that should be considered during the practical development of VR training systems.

Appendix

See Table 5.

Table 5 Iitemized description of subscales

Category	Subscale	Source	α value	Item	CITT
External Variables	Computer Self-efficacy	Compeau and Higgins (1995), Turan and Cetintas (2020)	0.838	I could complete a training task if there was no one around me to tell me what to do	0.676
				I could use an experimental tool if I had sufficient time	0.745
				I could complete an operation if there was someone giving me step-by-step instructions	0.732
				I could complete a training task if I had little built-in assistance	0.754
	Experimental Fidelity	Dalgarno and Lee (2010), Merchant et al. (2012)	0.873	The visual display quality of the virtual objects in VR distracted me from performing the assigned tasks	0.692
				Operations of the instruments in VR seemed like real operations to me	0.745
				There were times when the VR environment became more real and present for me than the real world	0.732
				There was a direct close connection between the operations and expected changes of outcomes	0.754

Table 5 (continued)

Category	Subscale	Source	α value	Item	CITT
	Learner Interaction		0.873	I was able to examine the object structures closely	0.714
				I was easily able to examine the object structures from multiple viewpoints	0.748
				I was easily able to manipulate the object structures and obtained feedback from them	0.724
				I was able to explore more functions with the hints and manuals	0.727
	Subjective Norm	Venkatesh and Bala (2008), Venkatesh et al. (2003)	0.800	I will use the VR training system if my classmates and friends around me are using it	0.641
				I will try to use the VR training system if my classmates and friends recommend that I do so	0.699
				I will use the VR training system if the teacher advises me to do so	0.601
	Facilitating Conditions		0.867	High computer network bandwidth is conducive to my use of the VR training system	0.691
				VR devices and high-performance software will make it appealing to use the VR training system	0.726
				The operating manual will make it easier for me to adapt to VR training	0.715
				I hope to be trained with respect to technology before I am exposed to the VR training system	0.637
				I hope I can ask someone for instant help if I get stuck in operating the system	0.681
Mediator Variables	Perceived Usefulness		0.889	I think the use of VR training systems can deepen my understanding and knowledge	0.712
				I think the use of VR training systems will enable me to get higher scores on the test	0.781
				I think the use of VR training systems can improve the efficiency of experimental operations	0.807
				I think the use of VR training systems can solve many problems in the experiment	0.733
	Perceived Ease of Use		0.817	I think it is easy to practice skills using VR training systems	0.623
				There is no need to spend too much effort on the use of VR training systems	0.719
				It is easy for me to address the problems encountered in VR training systems	0.668
	Perceived Immersion	Cheng and Tsai (2020), Jennett et al. (2008)	0.855	My attention was focused when I was exposed to the VR environment	0.735
				was so involved that I lost track of time	0.763
				Operations in the VR training system affect my enjoyment	0.739

Table 5 (continued)

Category	Subscale	Source	α value	Item	CITT
				Learning with the VR training system is more interesting than going to the laboratory	0.568
Outcome Variable	Behavioral Intention	Venkatesh and Bala (2008)	0.827	If possible, I plan to use the VR training system in the future	0.719
				I will try to suggest other classmates to use the VR training system	0.674
				I expect extended use of the VR training system during my learning	0.663

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Declarations

Conflict of interest The authors declare they have no conflicts of interest.

Data availability The data that support the findings of this study are available from the corresponding author upon reasonable request.

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