*Journal of Computational Design and Engineering*, 2023, **10**, 2036–2048
DOI: 10.1093/jcde/qwad091
Advance access publication date: 12 October 2023
Research Article

# Effects of building information modeling prior knowledge on applying virtual reality in construction education: lessons from a comparison study

Xingbin Chen[1], Sining Li[2], Gengying Li[1], Bin Xue[3], Bingsheng Liu[3], Yuan Fang[4], JoonOh Seo[5], Inhan Kim[6] and Jung In Kim[2,*]

[1]College of Water Conservancy and Civil Engineering, South China Agricultural University, Tianhe District, Guangzhou, Guangdong 510642, China
[2]Department of Architecture and Civil Engineering, City University of Hong Kong, Tat Chee Avenue, Kowloon 999077, Hong Kong SAR, China
[3]School of Public Policy and Administration, Chongqing University, No. 174, Shazheng Street, Shapingba District, Chongqing 400044, China
[4]School of Civil and Transportation Engineering, Guang Dong University of Technology, Guangzhou, Guangdong 510006, China
[5]Department of Building and Real Estate, The Hong Kong Polytechnic University, 11 Yuk Choi Rd, Kowloon 999077, Hong Kong SAR, China
[6]Department of Architecture, Kyung Hee University, Gyeonggi-do 17104, South Korea
*Correspondence: jungikim@cityu.edu.hk

## Abstract

Applying building information modeling (BIM) and virtual reality (VR) in construction education is an effective way to achieve better study motivation, learnability, creativity, and observation of the real world. However, whether different levels of BIM prior knowledge affect students' VR experimental learning, if at all, has not been examined. Therefore, this study employs a teaching intervention experiment to access the VR learning process based on the BIM prior knowledge. A total of 47 students, from the Department of Architecture and Civil Engineering, City University of Hong Kong, participated in the experiment. They were grouped according to whether they had taken the prior BIM tutorial section, with 23 participants in the group having completed the tutorial and 24 participants in the group that had not. Experiment materials were created and rendered via Autodesk Revit and Iris VR; the materials supported three tasks related to the underground design review scenarios and three other tasks about site planning review scenarios. After the experiment, a comparison study was done to discuss their differences based on VR task performances and satisfaction. The results revealed that the BIM prior knowledge mediated both the two-dimensional and three-dimensional navigations when students performed the tasks. Moreover, the relationship differences within the satisfactions showed that BIM prior knowledge effectively affected the learning outcomes. In conclusion, the comparison study implies that students' BIM prior knowledge is efficacious in the students' VR task performance and their VR satisfaction from cognitive and memory perspectives.

**Keywords:** construction education, building information modeling, virtual reality, prior knowledge

## 1. Introduction

Virtual reality (VR) has been shown to be a promising environment for assisting students' comprehension of lecture material in construction education and learning (Lucas & Gajjar, 2022; Park & Koo, 2022). Although building information modeling (BIM) has revolutionized the architecture, engineering, and construction (AEC) industry, studies have shown that such a shift from the vision of project information realization can achieve its full potential by leveraging both BIM and VR (Alizadehsalehi *et al*., 2020; Kim *et al*., 2021; Scheffer *et al*., 2018). In terms of construction education, the importance of students' learning outcomes cannot be overstated, particularly due to the widespread use of virtual design and construction in the field of construction education (Yoon *et al*., 2015). Such learning refers to not only a sense of spatial immersion but also the cognitive psychology and human memory system involved in learning (Weibel & Wissmath, 2011). Spatial immersion is the sense of being present in a virtual environment, which depends on the quality and consistency of the visual, auditory, and haptic stimuli provided by the VR (De Paolis & De Luca, 2022). The realistic and interactive virtual scene it creates can also influence the cognitive psychology of students in spatial orientation, attention, and problem-solving (Hruby *et al*., 2020; Zhao *et al*., 2020). Cognitive psychology refers to human mental processes, such as learning, reasoning, and decision-making (Lachman *et al*., 2015). Immersive and engaging learning environments can also enhance students' memory retention and transfer (Azarby & Rice, 2022). The human memory system is the mechanism that enables the storage and retrieval of information in the brain (Loftus, & Loftus, 2019). VR can affect students' memory systems by altering the encoding and consolidation of information, by providing multi-sensory and emotional experiences that increase the salience and distinctiveness of the information.

Adopting virtual design and construction in construction courses has been statistically shown to enhance study motivation, learnability, creativity, and observation of the real world; it has also been found that additional efforts are needed to deal with the issues related to the BIM prior knowledge (Alizadehsalehi *et al*., 2019). The existing research works revealed that prior perceptions of knowledge shall affect students' ability in new learning i.e., what the students already know or have experienced, would be "activated" by using them in the analysis and prediction (Ambrose *et al*., 2010; Johri & Olds, 2014). However, an anal-

**Received:** August 9, 2023. **Revised:** October 4, 2023. **Accepted:** October 4, 2023

ysis of how students' BIM prior knowledge (i.e., prior perception from their long-term nondeclarative memory) mediates the students' VR task performances and their VR satisfaction is still not clear but is likely substantial. That is whether students connecting their BIM prior knowledge to VR study would affect their VR performances and satisfaction, because of previous acquisition of three-dimensional (3D) model controlling and reasoning, etc. When VR is integrated into courses, if the students lack the BIM prior knowledge (e.g., a 3D experience), they may not effectively explore the VR learning task without the help of their perceptual priming. Nevertheless, it may cause the students to encounter mentally extraneous cognitive load and have negative impacts on working memory (Hsu *et al.*, 2017), thereby reducing the available cognitive resources for processing the relevant information and integrating it with BIM prior knowledge when working with new software or platforms. Working memory is very limited in its capacity and duration, so any unnecessary load can impair learning and performance, which would affect their VR satisfaction and task performance (i.e., confidence in completing the tasks without errors). Therefore, understanding the relationships among BIM prior knowledge, VR task performance, and satisfaction is important for enabling instructors to produce better course design, especially as existing knowledge has not depicted and revealed such relationships. Further exploration is warranted to better understand students' VR learning outcomes.

Given the volume of BIM and VR applications in construction education, research should explore their effects on the relevant students because such applications are expected to improve course design knowledge about the relationships among students' BIM prior knowledge, VR task performances, and VR satisfaction. Therefore, the students who participated in this study were undergraduates majoring in construction engineering and management. The experiments involved instruments that measured students' performances associated with the tutorial task to obtain a broader understanding of students' behavior; survey questionnaires were conducted to associate the findings with their VR satisfaction.

## 2. Theoretical Points of Departure

This study reviewed three main areas relevant to this research: (i) BIM and VR in construction education and learning, (ii) prior knowledge's effect on learning performance, and (iii) prior knowledge's effect on learning satisfaction.

### 2.1. BIM and VR in construction education

BIM, the significant and promising change in the AEC digital information format, has been widely adopted in construction projects as it produces a data-rich model and shifts the AEC industry from a vision to a realization (Scheffer *et al.*, 2018; Volk *et al.*, 2014). The broad adoption of BIM in the industry has created the need and increased its use within higher education curricula in order to prepare students succeed in their future career competition (Badrinath *et al.*, 2016; Puolitaival & Forsythe, 2016). Embedding BIM into existing and new courses with related workshops has been recognized as helping students' comprehension of the complex construction product and workflow process (Huang, 2018; Sacks & Pikas, 2013). Although BIM provides a digital format with a degree of simulation and visualization (i.e., desktop-based 3D), its project information has not been entirely presented on a real scale or supported users' physical walk-through on a practical scale, in which a sense of presence supports the navigation of the real-scale structure or construction site (Alizadehsalehi *et al.*, 2020). It also necessitates immersive techniques that support users' interactions with spatial components and other details from the model, including observing them from multiple educational perspectives. VR offers one solution to these issues (Alizadehsalehi *et al.*, 2020; Huang *et al.*, 2020; Radianti *et al.*, 2020).

VR, as one of the immersive technologies, is capable of offering sensations such as realistic images and sounds and simulating the user's physical presence in its software environment (Auyeskhan *et al.*, 2023; de Groot *et al.*, 2020). Since 2005, VR has been increasingly employed in both the AEC industry and education fields (Alizadehsalehi *et al.*, 2020; Sun *et al.*, 2019). Leveraging both the BIM and VR technologies within construction courses, the BIM model can be brought into the virtual space by VR, which provides students with an interactive experience (e.g., walk-through) with a realistic scale of structure or construction site in a safe and simulated environment (Li *et al.*, 2018; Wong *et al.*, 2020). Students involved in such a course are capable of facilitating on-site planning and design analysis as well as interactive presentations for better collaboration in their group project (Du *et al.*, 2018; Fu & Liu, 2018; Muhammad *et al.*, 2019). In addition, they can better understand the complex design, depict its issues, and reach better scenario decisions (Lee *et al.*, 2023; Romano *et al.*, 2019; Sutcliffe *et al.*, 2019).

### 2.2. Prior knowledge's effect on learning performance

Prior knowledge is the information a student already has before they learn new contexts, and research has revealed that prior knowledge affects students' ability in new learning as what students already know or have experienced, would be "activated." (Ambrose *et al.*, 2010; Johri & Olds, 2014). The result is human memory, which has been created by one exposure or by the repetition of information, experiences, and/or actions (Gazzaniga *et al.*, 2018). According to the time course factor, memory can be characterized as sensory memory, short-term and working memory, long-term declarative memory, and long-term nondeclarative memory (Gazzaniga *et al.*, 2018). *Sensory memory* refers to a very brief recall of a sensory experience, such as what a human just saw or heard, which lasts for about three seconds (Emmerson, 2017). *Short-term memory* allows a human to recall information to which they were just exposed (Gazzaniga *et al.*, 2018). *Working memory*, developed to extend the short-term memory, describes the kinds of mental processes involved when information is retained over a period of seconds to minutes (Hasson *et al.*, 2015). *Long-term declarative memory* (i.e., explicit memory) stores facts, knowledge, and events that can be consciously recalled and declared (Perera, 2021). *Long-term nondeclarative memory*, also known as implicit memory that cannot be declared, is disclosed when previous experiences facilitate performance on a task without requiring the intentional recollection of the experiences (Kump *et al.*, 2015).

Procedural memory, one type of long-term nondeclarative memory, refers to motor controls (i.e., skills and habits) and allows for the integration of sensory information and the coordination of movement (Du *et al.*, 2022). It enables activities that, once learned, can be performed automatically and without conscious thought (Janacsek & Nemeth, 2022). Procedural memory can affect an individual's response set by shaping their way of responding to certain stimuli based on previous experience (Chen *et al.*, 2022). The response set refers to the range of behaviors or actions that an individual can exhibit in response to a particular stimulus or situation (Risko, 2010). It is the collection of possible responses that a person can make based on their previous experiences, learned behaviors, and cognitive processes. An example is the tendency for a student to respond to a scenario question rather than directly answering. Prior knowledge formalized in an individual's procedural memory may either help or impede the new learning, such as by analogizing from BIM (desktop-based 3D controlling) to VR without recognizing the limitations of the analogy (Ambrose *et al.*, 2010).

## 2.3. Prior knowledge's effect on learning satisfaction

Perceptual priming is one form of long-term nondeclarative memory that refers to a change in responding to a stimulus (Bouyeure & Noulhiane, 2020). Perceptual priming is mediated by the perceptual priming system (Gazzaniga *et al.*, 2018). Within the perceptual priming system, the structure and form of objects and words can be primed by prior experience (Gazzaniga *et al.*, 2018). Studies reveal that the effects of perceptual priming can persist for 48 weeks when the stimulus is visualized in picture form (Mitchell *et al.*, 2018). It affects a student in perceiving information from a designated learning process, as the student may become either satisfied or frustrated when engaging with certain types of learning material (Dosher & Lu, 2017; Michael *et al.*, 2014).

In addition, working memory represents a limited-capacity store for retaining information over the short term (maintenance) and for performing mental operations on the contents of this store (Becker *et al.*, 2021). The contents of working memory could originate from sensory inputs such as visual sense (Oh *et al.*, 2019). Students with lower working memory capacity may struggle to keep up with the demands of the task's environment, leading to frustration and reduced satisfaction with the learning experience. In addition, students with poor working memory may struggle to retain and process new information, leading to feelings of confusion and discouragement (Carr, 2022).

## 2.4. Research question

The main research question addressed in this paper is whether students' different levels of BIM prior knowledge affect their VR experimental learning. Therefore, a comparison study was applied to explore the differences in the participating students' VR task performances and satisfaction. These aspects are introduced in ISO 9241–11, an international standard that provides a framework for accessing situations in which people use interactive systems (e.g., software or platforms). It measures the degree to which a system can be used by target users to achieve specified goals with standard components in a specific context of use, which can be referred to measure how well a student should interact with VR (ISO, 2018; Lewis & Sauro, 2018; Riihiaho, 2018).

*VR task performance*: measures the extent to which the student can complete the task within the maximum time of 15 minutes and the number of errors performed; and

*VR satisfaction*: measures the positive associations and absence of discontent that the student experiences after finishing the tasks. According to ISO 9241–11 (ISO, 2018), satisfaction is defined as "the extent to which the user's physical, cognitive, and emotional responses that result from the use of a system (e.g., software or platforms) meet the user's needs and expectations." It should enable comparisons across a range of contexts. A five-point Likert scale is used to provide a quantitative estimate of overall satisfaction from students' perspectives (e.g., immersion, manipulability, and capability).

# 3. Methods

Within this comparison study, the evaluation of VR task performance and satisfaction was measured based on human–computer interaction, which has been facilitated by the tools supporting education and learning (Ventayen *et al.*, 2018; Vertesi *et al.*, 2020). Therefore, Iris VR software was employed in the experiment, along with an accompanying virtual controller for students. HTC Vive Pro devices were used to display the VR content. Students then interacted with the VR using the tutorial tasks to enter and retrieve values as well as read different scenarios. The recordings were carefully coded using the metrics specified as the error on tasks. The session ended with the administration of the structural satisfaction survey. The methodology of this study was designed as follows (Fig. 1):

## 3.1. Experiment participants and materials

The study participants were undergraduates from the Department of Architecture and Civil Engineering, City University of Hong Kong. They were enrolled in undergraduate courses related to planning and managing construction projects. After their informed consent was obtained, 47 students were scheduled for individual evaluation sessions in the Built-informatics and Smart Cities Cluster Lab at the City University of Hong Kong. The participating students were grouped according to whether they had previously taken the BIM tutorial section. Group 1, who had not completed the tutorial, included 24 participants while Group 2, who had completed the tutorial, included 23 participants. Participants were allowed to stop the experiment whenever they felt uncomfortable. No participants were excluded because of severe motion sickness or the malfunction of the recording. Thus, the experiment maintained all 47 valid samples.

The experiment materials used in this study were the underground design of a residential building and the planning of a construction site, which were created and rendered via Autodesk Revit and Iris VR. The six representative tasks conducted in this research were designed based on those projects; three tasks related to underground design review scenarios, and the other three related to site planning review scenarios. These tasks were based on real case scenarios to simulate how students would interact with the virtual built environment, including pipe pile structural problems and spatial arrangements of the underground space as well as arrangement problems of the construction site. Participating students needed to finish the evaluation within the VR environment and provide their answers to the test facilitator; thus, their actual performance could be recorded as the tasks' success rate.

## 3.2. Experiment design

The experiment design of this study aimed to access the VR learning process based on BIM prior knowledge. Through the introduction and application of the proposed VR evaluation process to decrease individual variability in task performance due to knowledge about VR, data were collected from participants' interaction with the VR toward achieving task success.

Measures of VR task performance were defined based on ISO 9241–11 as follows (ISO, 2018). *Task completion* was determined by the extent of successful completion per task. Task completions are classified into three categories: (i) *completed with ease* when the stu-

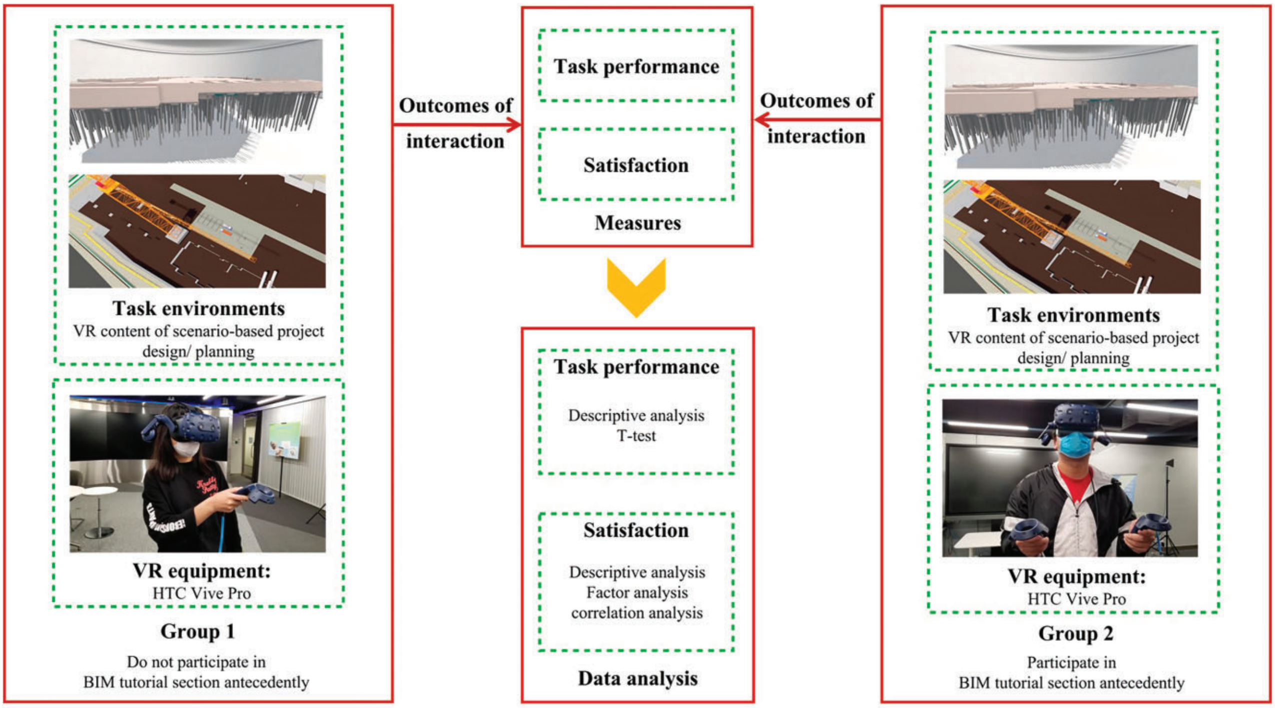


**Figure 1:** Research methodology of the comparison study.

dent was able to perform the task without any help from the test facilitator; (ii) *completed with difficulty* when the student achieved the task with minor difficulties and/or with minor hints from the test facilitator; and (iii) *failed to complete* when the student was unable to complete the task, even with some minor hints (e.g., they could not solve or committed errors preventing further progress). The *success rate* of task completion was determined by the percentage of tasks completed without errors.

After the VR experiment, every participating student immediately took a post-structural survey to evaluate their satisfaction in the lab. *Satisfaction* was measured using five-point Likert scale questions, in which students rated their level of agreement and scores were calculated by summing the scores on each of 10 aspects:

(i) S1 has a good immersive experience in an artificial environment through human senses (e.g., gets a more direct feel of the depth and volume of the design/planning by viewing it in the stereoscopic display and at full scale; Liu *et al.*, 2014; Natephra *et al.*, 2017; Wang *et al.*, 2018);
(ii) S2 feels fatigued when performing tasks (Lee & Sohn, 2018; Paes *et al.*, 2017);
(iii) S3 feels dizzy when performing tasks (Lee & Sohn, 2018; Paes *et al.*, 2017);
(iv) S4 has a good manipulation of direction vertically and horizontally, decelerating and accelerating the moving speed when navigating the design/planning (Du *et al.*, 2018; Fogarty *et al.*, 2015, 2018);
(v) S5 increases motivation in learning by manipulating and interacting with objects in a virtual environment (Alizadehsalehi *et al.*, 2019; Pedro *et al.*, 2016);
(vi) S6 presents the information appropriately, meaning words and symbols in the toolbar are easy to read and instructions respond fast enough (Pedro *et al.*, 2016; Santos *et al.*, 2014);
(vii) S7 presents appropriate VR features converted from the native 3D model (Alizadehsalehi *et al.*, 2019; Natephra *et al.*, 2017; Wang *et al.*, 2018);
(viii) S8 provides good visual feedback when grasping objects in the virtual environment (Geiger *et al.*, 2018; Wang *et al.*, 2018);
(ix) S9 brings value to learning, understanding, and reviewing the design/planning while walking through the virtual environment more effectively (Liu *et al.*, 2014; Fogarty *et al.*, 2018; Wang *et al.*, 2018); and
(x) S10 brings value to practicing the tasks in a safe environment, compared with traditional site visits (Alizadehsalehi *et al.*, 2019; Pedro *et al.*, 2016).

### 3.3. Data analysis

After collecting the data about task performance and satisfaction from both groups' experiments, a descriptive analysis (e.g., percentile values, standard deviation) was conducted to determine the task completion distribution, success rate, and satisfaction scoring. A *t*-test was then used to compare the means of task performance between two independent groups. The satisfaction results, based on the five-point Likert scale, were explored by factor analysis to identify the relationships between variables with possible dimension reductions—namely, grouping the satisfaction factors (i.e., dimensions) for further analysis. Based on the grouping results from the factor analysis, a correlation analysis was conducted to assess the relationships of factors across different dimensions as well as the relationship differences between both student groups' experiments.

## 4. Results and Discussion

Descriptive statistics such as means and *t*-test as well as factor and correlation analyses were calculated in SPSS using the task performance and satisfaction results.

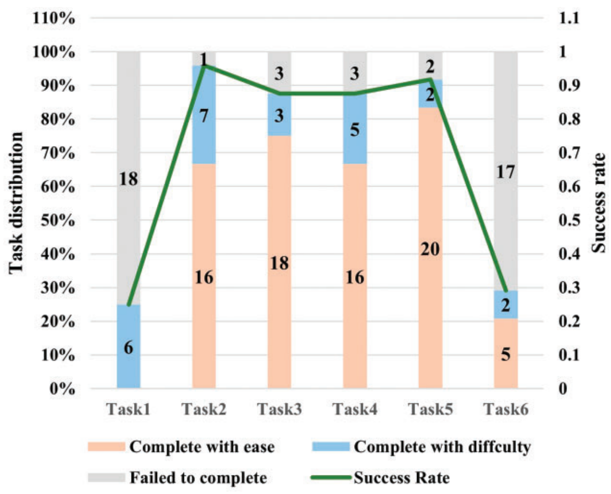


**Figure 2:** Task distribution and success rate of Group 1.

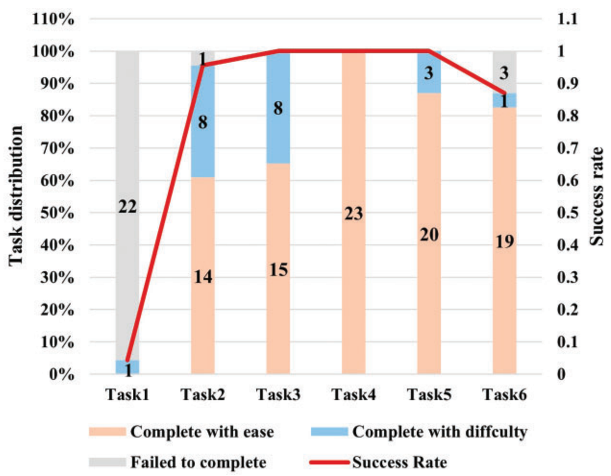


**Figure 3:** Task distribution and success rate of Group 2.

## 4.1. Comparison of task performances

The completion results are presented in Figs 2 and 3. The success rates mirroring task completions of the two groups show the differences in Task 1 (0.207 difference), Task 2 (0.002 difference), Task 3 (0.125 difference), Task 4 (0.125 difference), Task 5 (0.083 difference), and Task 6 (0.578 difference). To better understand the differences in task completion level, scores were assigned to the completion levels in order to process the independent samples *t*-test based on the Chinese grade equivalencies (i.e., 60 is the passing mark). Therefore, “complete with ease” was assigned 100, “complete with difficulty” was assigned 60, and “failed to complete” was assigned 0.

The independent samples *t*-test (Tables 1 and 2) reveals that Tasks 1 and 4 are significantly different between the two groups. Table 1 shows that the *t*-test results indicate the significance (2-tailed) of the independent sample *t*-test at 0.047 ($P \leq 0.05$) for Task 1, and 0.007 ($P \leq 0.05$) for Task 4. The two groups differed in task completion level considering BIM prior knowledge. This result corresponded to the task distribution results (Figs 2 and 3). In Task 1, the number of “complete with difficulty” dropped from six to one. In addition, the number of “failed to complete” increased from 18 to 22.

**Table 1:** Comparison of task performance between two groups (independent sample *t*-test).

| Task no. | | Levene’s test for equality of variances | | *t*-Test for equality of means | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | F | Sig. | t | df | Sig. (2-tailed) | Mean difference | Std. error difference | 95% Confidence interval of the difference | |
| | | | | | | | | | Lower | Upper |
| Task 1 | Equal variances assumed | 23.413 | 0 | 2.033 | 45 | 0.048 | 12.391 | 6.097 | 0.112 | 24.67 |
| | Equal variances not assumed | | | 2.061 | 33.046 | 0.047 | 12.391 | 6.013 | 0.159 | 24.624 |
| Task 2 | Equal variances assumed | 0.08 | 0.778 | 0.321 | 45 | 0.75 | 2.428 | 7.573 | − 12.826 | 17.681 |
| | Equal variances not assumed | | | 0.32 | 44.817 | 0.75 | 2.428 | 7.577 | − 12.835 | 17.69 |
| Task 3 | Equal variances assumed | 2.969 | 0.092 | − 0.436 | 45 | 0.665 | − 3.587 | 8.23 | − 20.163 | 12.989 |
| | Equal variances not assumed | | | − 0.441 | 36.583 | 0.662 | − 3.587 | 8.138 | − 20.082 | 12.908 |
| Task 4 | Equal variances assumed | 44.987 | 0 | − 2.884 | 45 | 0.006 | − 20.833 | 7.224 | − 35.384 | − 6.283 |
| | Equal variances not assumed | | | − 2.947 | 23 | 0.007 | − 20.833 | 7.069 | − 35.457 | − 6.21 |
| Task 5 | Equal variances assumed | 4.326 | 0.043 | − 0.955 | 45 | 0.345 | − 6.449 | 6.754 | − 20.052 | 7.154 |
| | Equal variances not assumed | | | − 0.968 | 32.912 | 0.34 | − 6.449 | 6.66 | − 20.001 | 7.103 |
| Task 6 | Equal variances assumed | 3.578 | 0.065 | − 5.245 | 45 | 0 | − 59.384 | 11.323 | − 82.189 | − 36.579 |
| | Equal variances not assumed | | | − 5.267 | 43.989 | 0 | − 59.384 | 11.275 | − 82.107 | − 36.661 |

**Table 2:** Performance means between two groups.

| Task no. | Group | N | Mean | Std. deviation | Std. error mean |
|---|---|---|---|---|---|
| Task 1 | Group 1 | 24 | 15 | 26.54 | 5.417 |
| | Group 2 | 23 | 2.61 | 12.511 | 2.609 |
| Task 2 | Group 1 | 24 | 84.17 | 25.693 | 5.245 |
| | Group 2 | 23 | 81.74 | 26.225 | 5.468 |
| Task 3 | Group 1 | 24 | 82.5 | 34.547 | 7.052 |
| | Group 2 | 23 | 86.09 | 19.479 | 4.062 |
| Task 4 | Group 1 | 24 | 79.17 | 34.631 | 7.069 |
| | Group 2 | 23 | 100 | 0 | 0 |
| Task 5 | Group 1 | 24 | 88.33 | 29.439 | 6.009 |
| | Group 2 | 23 | 94.78 | 13.774 | 2.872 |
| Task 6 | Group 1 | 24 | 25.83 | 42.315 | 8.638 |
| | Group 2 | 23 | 85.22 | 34.755 | 7.247 |

## 4.2. Comparison of satisfaction

The distribution of satisfaction ratings for Groups 1 and 2 is shown in Figs 4 and 5. To analyze the student satisfaction outcomes, scores were assigned to S2 and S3: "strongly agree" was assigned 1, "agree" was assigned 2, "neutral" was assigned 3, "disagree" was assigned 4, and "strongly disagree" was assigned 5. In addition, scores were assigned to S1 and S4–10: "strongly agree" was assigned 5, "agree" was assigned 4, "neutral" was assigned 3, "disagree" was assigned 2, and "strongly disagree" was assigned 1.

To investigate the satisfaction factor modeled with dimension structure, a factor analysis was used to explore the correlated criteria and the unobserved dimensions among all 47 students. Before the actual factor analysis process, it was necessary to verify the suitability of the factor analysis to the data collected (Table 3).

**Table 3:** KMO and Bartlett's test.

| KMO measure of sampling adequacy | | 0.592 |
|---|---|---|
| Bartlett's test of sphericity | Approx. Chi-square | 201.203 |
| | df | 45 |
| | Sig. | 0 |

*Note*. Determinant = 0.08.

*Identify determinant of the correlation matrix*: This determinant is an indicator of the degree of correlations between variables. As Field (2013) pointed out, a small determinant assumes the existence of variables with very high correlations with one another, indicating that the data may be suitable for factor analysis. In this study, the determinant obtained a low value of 0.08 (≥ 0.00 001), indicating the existence of high correlations between the variables, making it possible to apply this technique.

*Kaiser–Meyer–Olkin (KMO) sample-fit measure*: This test compares the magnitudes of correlation coefficients observed in the correlation matrix with the magnitudes of correlation coefficients observed in the anti-image correlation matrix. This value was 0.592, so it is a meritorious value (Field, 2013) that advises the application of factor analysis as the value of the KMO test should be greater than 0.5.

*Bartlett's test of sphericity*: This test is used to verify the hypothesis that the correlation matrix is an identity matrix—a matrix

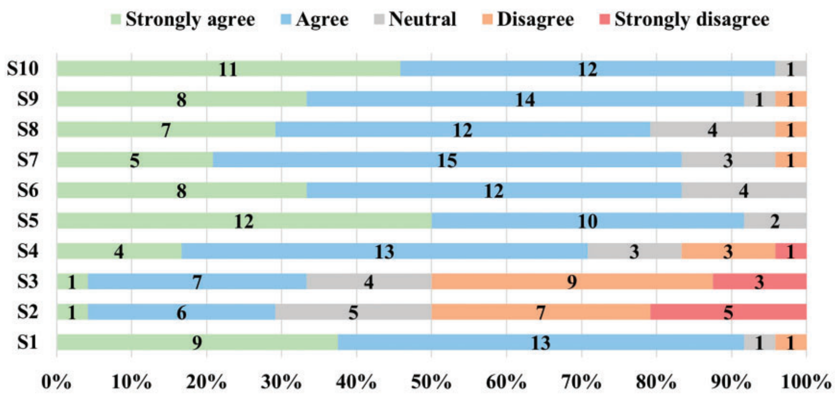


**Figure 4:** Satisfaction rating of Group 1.

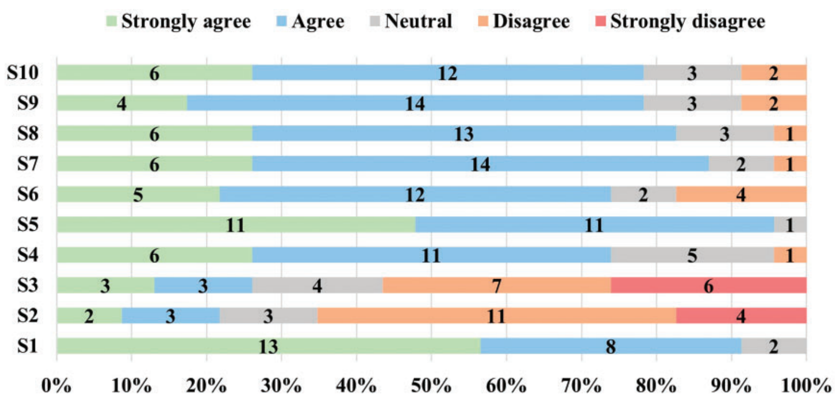


**Figure 5:** Satisfaction rating of Group 2.

**Table 4:** Total variance explained.

| Component | Initial Eigenvalues | | |
|---|---|---|---|
| | Total | % of Variance | Cumulative % |
| **1** | **3.949** | **39.49** | **39.49** |
| **2** | **1.749** | **17.491** | **56.982** |
| **3** | **1.224** | **12.24** | **69.222** |
| 4 | 0.808 | 8.081 | 77.303 |
| 5 | 0.691 | 6.906 | 84.208 |
| 6 | 0.459 | 4.593 | 88.802 |
| 7 | 0.44 | 4.401 | 93.202 |
| 8 | 0.358 | 3.584 | 96.786 |
| 9 | 0.205 | 2.052 | 98.838 |
| 10 | 0.116 | 1.162 | 100 |

**Table 5:** Rotated component matrix.

| Items | Component | | |
|---|---|---|---|
| | 1 | 2 | 3 |
| S9 | 0.906 | | |
| S10 | 0.79 | | |
| S6 | 0.777 | | |
| S7 | 0.684 | | |
| S5 | | 0.831 | |
| S4 | | 0.774 | |
| S1 | | 0.638 | |
| S2 | | | 0.918 |
| S3 | | | 0.917 |

whose primary diagonal is made up of ones (correlation of the item to itself), while the rest are zeros (null variables). The significance value obtained was 0.000, demonstrating significance (≤ 0.05), which indicates that the data matrix is suitable for factor analysis (Field, 2013).

After validating the suitability of the factor analysis, the component model is generated to get several major components equal to the number of initial variables. The main components are generated and kept according to the Kaiser–Guttman criteria (Table 4; Pallant, 2020). According to the Cattell scree test (Pallant, 2020), the characteristic values of all factors are drawn, and all factors above the critical point should be kept (i.e., the saddle of the diagram in Fig. 6).

Main components rotation (i.e., orthogonal rotation) is used to generate dimensions unrelated to or independent of each other (Pallant, 2020). The varimax rotation method is applied to minimize the number of variables with high absolute values of factor weights (Pallant, 2020). From the matrix of the structure generated in this study (Table 5), it can be concluded that nine variables were involved in this research: the first dimension is composed of four criteria, the second dimension is composed of three criteria, and the third dimension is composed of two criteria. Based on the structure of the variables that define the factors, Dimension 1 can be titled as effectiveness, Dimension 2 as manipulation, and Dimension 3 as comfort.

The independent samples *t*-test (Tables 6 and 7) reveals that all satisfaction results are not significantly different between the two groups. Their means show the difference in S10 (0.460 difference), S6 (0.384 difference), S9 (0.339 difference), S4 (0.290 difference), S1 (0.228 difference), S3 (0.185 difference), S2 (0.147 difference), S7 (0.087 difference), S5 (0.018 difference), and S8 (0.002 difference). Thus, more two criteria in Dimension 1 (effectiveness, 75%) and Dimension 2 (manipulation, 66.67%) were not consistent in satisfaction level. As for the different dimensions, the relationship differences between both student groups' experiments indicate the need for further correlation analysis to examine the measures involved. For Dimension 1 (effectiveness) – Dimension 2 (manipulation), the results in Table 8 show that S6 is significantly correlated with S5 in Group 1, which is not available in Group 2. In addition, there is no correlation between S10 and S4 in Group 1, which is different in Group 2. The results of Table 8 also show that S7 is not significantly correlated with S1 and S4 in Group 1, which is not the case in Group 2. Meanwhile, the other correlation analysis—namely, Dimensions 1–3 (Table 9) and Dimensions 2–3 (Table 10)—were not significant between measures for both student groups' experiments.

## 5. Discussion

Concerning the comparison results of the task performance, both Task 1 and Task 4 are problem-finding ones; BIM prior knowledge has a negative transfer on Task 1 but a positive transfer on Task 4. The positive transfer may be attributed to procedural memory offered by BIM prior knowledge. In this domain-specific task, students with BIM prior knowledge can better observe certain symptoms based on formalized habits and more easily find the crux

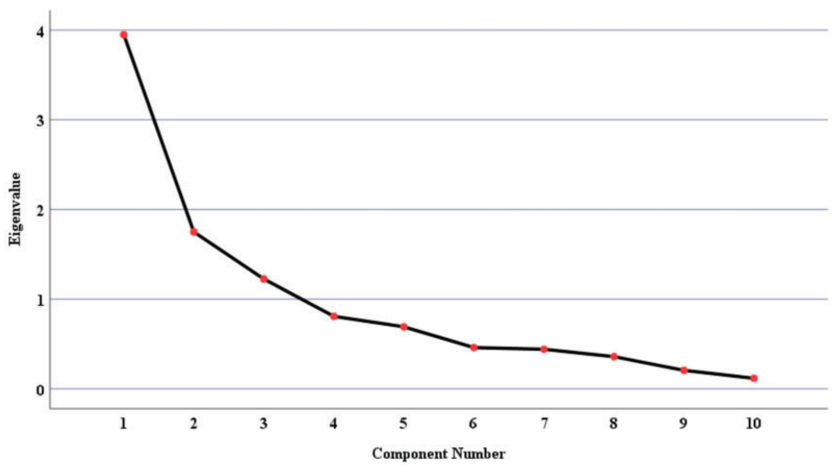


**Figure 6:** Scree test result.

**Table 6:** Comparison of satisfaction between the two groups based on the independent sample *t*-test.

| Satisfaction no. | | Levene's test for equality of variances | | *t*-Test for equality of means | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | F | Sig. | t | df | Sig. (2-tailed) | Mean difference | Std. error difference | 95% Confidence interval of the difference | |
| | | | | | | | | | Lower | Upper |
| S1 | Equal variances assumed | 0.059 | 0.809 | − 1.113 | 45 | 0.272 | − 0.228 | 0.205 | − 0.641 | 0.185 |
| | Equal variances not assumed | | | − 1.115 | 44.844 | 0.271 | − 0.228 | 0.205 | − 0.641 | 0.184 |
| S2 | Equal variances assumed | 0.147 | 0.703 | − 0.417 | 45 | 0.678 | − 0.147 | 0.352 | − 0.855 | 0.562 |
| | Equal variances not assumed | | | − 0.417 | 44.939 | 0.678 | − 0.147 | 0.352 | − 0.855 | 0.561 |
| S3 | Equal variances assumed | 0.795 | 0.377 | − 0.5 | 45 | 0.619 | − 0.185 | 0.369 | − 0.929 | 0.559 |
| | Equal variances not assumed | | | − 0.498 | 42.941 | 0.621 | − 0.185 | 0.371 | − 0.933 | 0.563 |
| S4 | Equal variances assumed | 1.515 | 0.225 | − 1.05 | 45 | 0.299 | − 0.29 | 0.276 | − 0.846 | 0.266 |
| | Equal variances not assumed | | | − 1.055 | 43.363 | 0.297 | − 0.29 | 0.275 | − 0.844 | 0.264 |
| S5 | Equal variances assumed | 0.371 | 0.546 | − 0.1 | 45 | 0.921 | − 0.018 | 0.182 | − 0.384 | 0.348 |
| | Equal variances not assumed | | | − 0.1 | 44.841 | 0.921 | − 0.018 | 0.181 | − 0.384 | 0.347 |
| S6 | Equal variances assumed | 1.676 | 0.202 | 1.531 | 45 | 0.133 | 0.384 | 0.251 | − 0.121 | 0.889 |
| | Equal variances not assumed | | | 1.52 | 39.346 | 0.136 | 0.384 | 0.253 | − 0.127 | 0.895 |
| S7 | Equal variances assumed | 0.13 | 0.72 | − 0.41 | 45 | 0.684 | − 0.087 | 0.212 | − 0.515 | 0.341 |
| | Equal variances not assumed | | | − 0.409 | 44.847 | 0.684 | − 0.087 | 0.212 | − 0.515 | 0.341 |
| S8 | Equal variances assumed | 0.129 | 0.721 | − 0.008 | 45 | 0.994 | − 0.002 | 0.23 | − 0.465 | 0.461 |
| | Equal variances not assumed | | | − 0.008 | 44.998 | 0.994 | − 0.002 | 0.23 | − 0.464 | 0.461 |
| S9 | Equal variances assumed | 0.024 | 0.877 | 1.511 | 45 | 0.138 | 0.339 | 0.224 | − 0.113 | 0.79 |
| | Equal variances not assumed | | | 1.507 | 43.809 | 0.139 | 0.339 | 0.225 | − 0.114 | 0.792 |
| S10 | Equal variances assumed | 0.161 | 0.69 | 2.125 | 45 | 0.039 | 0.46 | 0.217 | 0.024 | 0.896 |
| | Equal variances not assumed | | | 2.107 | 38.051 | 0.042 | 0.46 | 0.218 | 0.018 | 0.902 |

**Table 7:** Satisfaction means between two groups.

| Satisfaction no. | Group | N | Mean | Std. deviation | Std. error mean |
|---|---|---|---|---|---|
| S1 | Group 1 | 24 | 4.25 | 0.737 | 0.15 |
| | Group 2 | 23 | 4.48 | 0.665 | 0.139 |
| S2 | Group 1 | 24 | 3.38 | 1.209 | 0.247 |
| | Group 2 | 23 | 3.52 | 1.201 | 0.25 |
| S3 | Group 1 | 24 | 3.25 | 1.152 | 0.235 |
| | Group 2 | 23 | 3.43 | 1.376 | 0.287 |
| S4 | Group 1 | 24 | 3.67 | 1.049 | 0.214 |
| | Group 2 | 23 | 3.96 | 0.825 | 0.172 |
| S5 | Group 1 | 24 | 4.42 | 0.654 | 0.133 |
| | Group 2 | 23 | 4.43 | 0.59 | 0.123 |
| S6 | Group 1 | 24 | 4.17 | 0.702 | 0.143 |
| | Group 2 | 23 | 3.78 | 0.998 | 0.208 |
| S7 | Group 1 | 24 | 4 | 0.722 | 0.147 |
| | Group 2 | 23 | 4.09 | 0.733 | 0.153 |
| S8 | Group 1 | 24 | 4.04 | 0.806 | 0.165 |
| | Group 2 | 23 | 4.04 | 0.767 | 0.16 |
| S9 | Group 1 | 24 | 4.21 | 0.721 | 0.147 |
| | Group 2 | 23 | 3.87 | 0.815 | 0.17 |
| S10 | Group 1 | 24 | 4.42 | 0.584 | 0.119 |
| | Group 2 | 23 | 3.96 | 0.878 | 0.183 |

of the problem. When completing Task 4 related to the site planning scenario, students only needed to navigate within the same floor level (2D plane). However, when working on Task 1 of the underground structure, students needed to walk through different floor levels (3D space). The model manipulation within the VR environment is not consistent with that within BIM. Therefore, the negative transfer may be the response set impacted by BIM prior knowledge, suggesting that the response set is influenced by the student's past BIM experiences. Overall, the response set is a fundamental concept in cognitive learning theory, as it helps explain how individuals acquire and use new information to guide their behavior in different situations. Students with BIM prior knowledge have limitations in responding to their virtual presence in the VR (i.e., the environment in which they find themselves), due to their tendency to control the 3D model in BIM. This finding indicates that students were having difficulties walking and locating the designed cracked pile of the underground structure in the VR.

In terms of the comparison results for satisfaction, the correlation between S6 and S5 reveals that, for students without BIM prior knowledge, their learning incentives are positively related to their rating of the VR interface. This finding is attributed to the perceptual priming system, as different perceptual priming, plays a role in the relationship between interface perception and motivation. In other words, perceptual priming may affect students' attention and memory for interface stimuli. Such priming can have positive effects, such as facilitating learning and comprehension, but it can also have negative effects, such as creating biases and stereotypes. However, the results also suggested that

**Table 9:** Dimension 1 (effectiveness) – Dimension 3 (comfort).

| | | Group 1 | | Group 2 | |
|---|---|---|---|---|---|
| | | S2 | S3 | S2 | S3 |
| S6 | Pearson correlation | 0.179 | 0.108 | 0.023 | 0.105 |
| | Sig. (2-tailed) | 0.402 | 0.617 | 0.917 | 0.633 |
| | N | 24 | 24 | 23 | 23 |
| S7 | Pearson correlation | 0.1 | 0.209 | 0.049 | 0.276 |
| | Sig. (2-tailed) | 0.643 | 0.327 | 0.823 | 0.202 |
| | N | 24 | 24 | 23 | 23 |
| S9 | Pearson correlation | 0.056 | −0.065 | −0.16 | 0.053 |
| | Sig. (2-tailed) | 0.795 | 0.761 | 0.467 | 0.811 |
| | N | 24 | 24 | 23 | 23 |
| S10 | Pearson correlation | −0.108 | −0.032 | 0.022 | 0.205 |
| | Sig. (2-tailed) | 0.616 | 0.881 | 0.919 | 0.349 |
| | N | 24 | 24 | 23 | 23 |

**Table 10:** Dimension 2 (manipulation) – Dimension 3 (comfort).

| | | Group 1 | | Group 2 | |
|---|---|---|---|---|---|
| | | S2 | S3 | S2 | S3 |
| S1 | Pearson correlation | 0.183 | 0.077 | 0.129 | 0.209 |
| | Sig. (2-tailed) | 0.392 | 0.721 | 0.559 | 0.338 |
| | N | 24 | 24 | 23 | 23 |
| S4 | Pearson correlation | −0.137 | −0.216 | 0.299 | 0.338 |
| | Sig. (2-tailed) | 0.523 | 0.311 | 0.165 | 0.115 |
| | N | 24 | 24 | 23 | 23 |
| S5 | Pearson correlation | −0.041 | 0.029 | 0.179 | 0.205 |
| | Sig. (2-tailed) | 0.848 | 0.893 | 0.415 | 0.349 |
| | N | 24 | 24 | 23 | 23 |

**Table 8:** Dimension 1 (effectiveness) – Dimension 2 (manipulation).

| | | Group 1 | | | Group 2 | | |
|---|---|---|---|---|---|---|---|
| | | S1 | S4 | S5 | S1 | S4 | S5 |
| S6 | Pearson correlation | .504[b] | 0.315 | .505[b] | .643[a] | 0.375 | 0.322 |
| | Sig. (2-tailed) | 0.012 | 0.134 | 0.012 | 0.001 | 0.078 | 0.134 |
| | N | 24 | 24 | 24 | 23 | 23 | 23 |
| S7 | Pearson correlation | 0.327 | 0.229 | 0.092 | .656[a] | .533[a] | 0.329 |
| | Sig. (2-tailed) | 0.119 | 0.281 | 0.669 | 0.001 | 0.009 | 0.125 |
| | N | 24 | 24 | 24 | 23 | 23 | 23 |
| S9 | Pearson correlation | .470[b] | 0.153 | 0.085 | .539[a] | 0.262 | 0.313 |
| | Sig. (2-tailed) | 0.02 | 0.475 | 0.695 | 0.008 | 0.228 | 0.147 |
| | N | 24 | 24 | 24 | 23 | 23 | 23 |
| S10 | Pearson correlation | .455[b] | −0.118 | −0.133 | .582[a] | .625[a] | 0.302 |
| | Sig. (2-tailed) | 0.026 | 0.582 | 0.536 | 0.004 | 0.001 | 0.162 |
| | N | 24 | 24 | 24 | 23 | 23 | 23 |

*Notes.*
[a]Correlation is significant at the 0.01 level (2-tailed).
[b]Correlation is significant at the 0.05 level (2-tailed).

direct VR did not privilege objective satisfaction evaluation, which is necessary to utilize the course design.

As for the correlation between S10 and S4, the finding may suggest that students who previously acquired taken the BIM experience and then navigated the VR—even when experiencing greater immersive navigation—are not more prone to VR as a safer learning manner. BIM prior knowledge provides them with better judgment related to safety issues and manipulation. This research may also provide insights into such a comparison and suggests that, if some students have yet to develop the 3D cognitive architecture for abstraction from BIM prior knowledge, their sense of walk-through suffers as greater mental effort is being spent, thereby resulting in lower scores (in this study, lower than Group 2). Furthermore, students without BIM prior knowledge may have overloaded working memory when facing a new external stimulus (e.g., 3D information of VR scenario), which thus impairs their learning (Blayney *et al.*, 2015). Such a situation can cause further stress that leads to negative effects on students both physically and emotionally.

Regarding the correlation between S7 and S1, there is one theory to describe how a human's mental image processes 3D information: visuospatial constructive cognition. Visuospatial constructive cognition is defined as one's ability to view the components of an object and construct a replica from these parts (Mervis *et al.*, 1999). As individual differences in visuospatial constructive ability and pattern construction improve with BIM prior knowledge, it may enhance students' sense of reality, thereby resulting in a better immersive experience. In this study, students with BIM prior knowledge had a better impression of the equivalent quality environment (scoring was higher than Group 1). Cognitive load and prefrontal cortex demand are of interest to this end as the cognitive structure may be underdeveloped in students with no BIM prior knowledge. This relationship is further complicated by cognitive research and its relationship to sensory memory available to the learner (Swaak & de Jong, 2001). In the VR-based task completion process, students who have BIM prior knowledge may have better working memory capacity for retaining the 3D information over a short term and supporting mental operations on the contents of this store (Becker *et al.*, 2021). They may experience better VR, which influences an individual's satisfaction.

Considering the objectives of this study, an acceptability evaluation was used to assess the extent to which experienced experts agree with the study and its results. The authors explained the proposed research to domain experts and asked them to rate its acceptability from their professional perspective on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). All of the participating experts, with average 16.4 working experience, agreed that both the study and its results were acceptable, with an average score of 4.6 (three participants scored it 5; two participants scored it 4). The experts made the following comments:

(i) The study is well-designed and uses a rigorous methodology to address the research questions.
(ii) The study has a sufficient and representative sample that increases the generalization of the findings.
(iii) The study uses valid and reliable data collection methods and measures that ensure its accuracy and consistency.
(iv) The study applies appropriate data analyses and tests that match the research question.
(v) The study draws reasonable and supported conclusions from the analysis and acknowledges the limitations and implications of the research.

## 6. Conclusions

Present construction education has leveraged BIM and VR in achieving better learning outcomes. However, existing research has not explored whether students' different levels of BIM prior knowledge affect their VR experimental learning, considering an immersive experience from the cognitive psychology and human memory system perspectives. The results of such research would serve as an important reference for future course design. This study contributed to addressing this research gap.

The key findings of this study, which comparing students with and without BIM prior knowledge, can be summarized as follows. The comparison of task performances showed that BIM prior knowledge has a negative transfer on Task 1 (3D navigation), but a positive transfer on Task 4 (2D navigation), suggesting that procedural memory offered by BIM prior knowledge can improve students' 2D observation with formalized motor controls. Such procedural memory better integrates the sensory information and coordinates the plane movements. The response set impacted by BIM prior knowledge limited students' response to their presence in the VR, due to their tendency to control the 3D model in BIM instead of virtual walking. This finding also implies that prior knowledge does not provide all new learning based on an equally solid foundation. When learning in a new environment, students can draw on prior knowledge that might not be appropriate for the context and, consequently, impede new learning.

The comparison of satisfaction showed that students without BIM prior knowledge positively related their learning incentives to their rating of the VR interface. Differences in perceptual priming can affect students' attention to and memory of interface stimuli. In addition, students who have BIM experience before navigating the VR—even when experiencing greater immersive navigation—are not more prone to VR as a safer learning manner. This finding can also provide insights into the comparison as it suggests that, if some students have yet to develop the 3D cognitive architecture for abstraction from BIM prior knowledge, their sense of walk-through suffers as greater mental effort is being spent. Working memory overload can negatively affect students' well-being. For students with BIM prior knowledge, the quality of features offers them better immersive experience because of their enhanced sense of reality and working memory.

Curriculum development efforts should consider the connection between new knowledge and the prior knowledge. Instruction should start with what the learner already knows. When newly learning within VR, students may draw on their BIM prior knowledge that can help or hinder their learning. To avoid distorting their interpretation of new material or impeding learning, in addition to deliberately activating students' BIM prior knowledge to strengthen appropriate associations, instructors shall (i) clearly explain the conditions and contexts of the applicability, (ii) point out differences as well as similarities when employing VR, and (iii) provide multiple examples and contexts concerning VR's effectiveness to support students' understanding.

The authors are cautiously confident in our findings because the measurement scales used in this study are reliable and valid for use in this study. Furthermore, the inferences based on this data analysis are limited by the fact that the study involved a relatively small sample and could not include outsourced students due to university-restricted assessments during the Coronavirus disease 2019 (Covid-19) pandemic. Thus, the findings may not adequately represent a general student population from the construction discipline. Given such a limitation, future research should involve a larger participant sample to ensure better generalizability and strengthen the interpretation of results. In addition to individual participation, future research could also examine the collaborative interactions and engagements for group participation.

## Acknowledgments

The research described in this paper is conducted with the support of the Guangdong Natural Science Foundation (Grant # 2022A1515110888), Guangdong Postgraduate Education Foundation (Grant # 2023SFKC_106), Guangzhou Natural Science Foundation (Grant # 2023A04J1560), South China University of Agriculture (Education Development Grants # K22192, K22055, and ZLGC21046), City University of Hong Kong (Grant # 7005656), and the Korea Agency for Infrastructure Technology Advancement (KAIA) grant funded by the Ministry of Land, Infrastructure and Transport (Grant RS-2021-KA163269) in 2023. The authors appreciate the support.

## Conflict of interest statement

None declared.

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**Received:** August 9, 2023. **Revised:** October 4, 2023. **Accepted:** October 4, 2023