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Task Complexity and Learning Styles in Situated Virtual Learning Environments for Construction Higher Education

Abstract: This paper contributes to the ongoing discussion and research on the role of 3D virtual learning environments in teaching and learning. It specifically focuses on the use of video games as an enabling technology in construction higher education. As such, it investigates whether task complexity has any influence on an individual's preferred learning style whilst learning through virtual reality (VR) technology. To answer this question and address relevant issues, an educational experiment has been designed and conducted. An experimental virtual learning environment, the *Situation Engine*, was set up as a virtual construction site for undergraduate construction students to experience construction work in progress. The design and development of the *Situation Engine* has drawn on powerful pedagogical theories such as situated and experiential learning. 253 undergraduate students participated in the educational experiment. Three tasks of different complexity levels were designed as the experimental environments; with level of complexity being the independent variable. The hypothesis that students would adopt different learning styles when engaged in learning tasks of different complexities was rejected. No significant difference in the preferred learning styles was identified among the three experimental groups. It was concluded, therefore, that when using virtual reality technology for construction education there is no evidence to suggest the level of task complexity has significant influence on how people learn. The study presented in this paper is the first empirical study in the construction higher education field that reveals the relationship between the task complexity and students learning styles when Virtual Learning Environments are engaged.

1. Introduction

Human experience of physical space stands on the verge of not only a technical revolution, but on the edge of how we emotionally and cognitively experience our built environment [1]. A particular consequence of this human-technological integration is the further blending of virtual space with real space, both in actual and perceptual terms. This consequence brings challenges and opportunities to the learning and teaching of architecture and construction in particular – a field intensely related to how we perceive, learn and understand spaces and buildings.

Virtual reality (VR) technology, as a simulation that represents the real world, is of great interest when exploring and investigating how emerging digital technologies impact the way people experience the world in a learning context [2,3]. The three-dimensional (3D) environments are believed to be beneficial for the building of knowledge in construction education [4]. However, there are ongoing debates on the role of computers and the VR technology as tools in learning and teaching [2,4,5,6]. In particular, how can we integrate the VR technology and the learning contexts to achieve the best learning outcome needs further investigation, as there is insufficient evidence to establish a guideline on designing Virtual Learning Environments (VLEs) for different learning contexts.

The majority of current research regarding VLEs and applications in construction education are related to the utilization of immersive visualization as an aid to improve students' understanding of building and to aid design tutors to explore students' projects to detect flaws. Despite rapid development of VR and other enabling technologies in construction education, there have been limited studies utilising a systematic investigation of the development of Virtual Environments in response to different learning and cognitive styles of their users (the students) [7, 8].

Learning styles are defined as characteristic features determining cognitive and psycho-social behaviour of learners, their perception of knowledge, interaction and processing of information in different learning environments [9]. Although the application of learning style theories in the development of new technology-driven pedagogical models is quite common, the application of these theories in the development of VLEs, or studies that explore the extent to which such VLEs help develop new learning styles, from a user-oriented perspective, are somewhat limited.

In construction learning and teaching, experiences of and with the built environment are particularly important and to gain such experiences usually requires the learner to be engaged with the physical environment. This is in line with Kolb's experiential learning theory which explicitly claims that people grasp and transform knowledge through experiences. Adopting Kolb's theoretical perspective, this paper particularly explores the potential of VLEs to create new virtual learning experiences in support of construction education. While doing so, it adopts a user-oriented approach, and as such, aims to develop a critical understanding of the correlation between preferred learning styles of students and complexity of tasks undertaken by the students while learning with VLEs.

The structure of the paper is as follows. After the introduction, Section 2 provides background information on VLEs and experiential learning. It characterizes the use of VLEs from a technical and pedagogical perspective. It then provides a review of literature on pedagogy, with a particular focus on experiential learning theory and the educational objectives which underline the main evaluation framework of the VLE developed for the purpose of this research (the Situation Engine). This section also provides the main theoretical and methodological grounding for the formulation of the main research questions. Section 3 clearly explains the research question together with the design of the research experiment, which draws on the mapping of Bloom's taxonomy onto Kolb's experiential learning model; outlining the main framework used in data collection and analysis in the following section. Section 4 gives a detailed account of how data was collected and analysed, and reports on the main findings of the experiments. Section 5 summarises the conclusions and implications while section 6 summarises limitations and future work.

2. Background

2.1 Virtual Learning Environments (VLEs)

The most generic description of3D immersive VLEs is the interactive 3D virtual environment, or virtual worlds [10]. The first virtual world was created in 1969 [11], but a significant step forward came with the launch of Sims Online[1] in 2002. In 2003, both SecondLife[1] and Unreal Tournament 2003 were launched and heralded in opportunities for users and educators to customise game worlds without requiring complex computer coding skills [12]. This major development in the accessibility of video game technology accelerated the quality, performance and functionality of virtual worlds in the context of learning [13]. Today, in the context of construction education, modified computer games are used in multi university undergraduate collaborative learning contexts [14], in post graduate courses in Integrated Project Delivery [15] and in lifelong learning contexts such as supporting practitioners in redevelopment assessment [16]. There is also much to learn through the application of computer gaming technology in other fields; medicine is a notable example as it was one of the first fields to adopt this kind of technology [17] and has been very active in development since employing the full range of Milgram's [18] "virtuality continium" [19, 20, 21].

[1] http://www.ea.com/au/sims
[1] http://secondlife.com/

Virtual Learning Environments (VLE) include a significant range and mix of technologies and provide a plethora of functionality, features and possibilities. Because the scope of the modalities in a VLE is known to be one of the most significant and direct influences on the effectiveness of a virtual world in teaching and learning terms, this review of the technology will focus on the best quality of modality available on a standard computer system – namely, video game technology. The video game is a technology that electronically simulates and manipulates digital images produced by a computer program or application, and projects the images on a monitor or on other forms of display such as head-mounted displays. The video game usually responds to user inputs and emphasises fast action (adapted from Oxford and Merriam-Webster online Dictionaries[2]). Steuer's [22] early assessment of the impact that video games were having still stands, he described them as the closest most people come to a media system that is both highly vivid and highly interactive. The notion of "serious video games" was introduced to form a bridge between the rapidly developing video game market and particular educational needs. The concept of a serious game was first defined by Clark Abt in his seminal work "Serious Games" [23]. Abt defines "serious games" as digital games that primarily aim at education, outreach or training rather than entertainment. As an alternative, interesting and more playful way to communicate information serious games have the potential to make the learning process more effective [24]. While the reputation of video games as being violent and shallow inhibited development in the early years growing scholarly attention, at around the same time as the increased ability of educators to build custom worlds using off the shelf game technology noted above, reinforced their potential for learning [25]. There are two key mechanisms to consider in any serious game: "game mechanics" and "learning mechanics". Game mechanics control a user's interaction with the game state [26]. Learning mechanics facilitate learning through a range of pedagogies and educational theories [27]. Arnab et al. [27] draw from the literature on game studies and learning theory to map between an abstracted set of game and learning mechanisms. A sample of game mechanics include: Behavioural Momentum/Role Play, Movement/Realism, Assessment, Strategy, Realism, Selecting/Collecting Tokens. A sample of learning mechanics include: Instructional/Guidance, Observation, Assessment, Simulation/Modelling, Planning [REF: Arnab, 2015]. They map onto each other as follows:

Learning Mechanics	**Game Mechanics**
Instructional/Guidance	Behavioural Momentum/Role Play
Observation	Selecting/Collecting Tokens
Simulation/Modelling	Movement/Realism
Assessment	Assessment
Planning	Strategy

Adapted from Arnab 2015 [27]

One is able to see these relationships in action in many serious games. In fact, the serious games literature emphasises many connections to established educational strategies and pedagogical theories [27, 28, 29, 30, 31]. The next section reviews the literature on pedagogy, including experiential learning theory and associated educational objectives to provide background on how one influential theory is able to be tested through a custom designed serious game.

2.2 Experiential Learning and Educational Objectives

[2] http://www.merriam-webster.com/dictionary/video%20gam

Experiential learning is a critical concept in the context of VR applied to learning [32, 33]. For decades researchers have been working on learning models and learning styles to enhance learners' learning experiences and outcomes. Kolb and Goldman [34] developed their experiential learning model (ELM) and learning styles inventory (LSI) in 1976. Since then both have become highly influential [35]. ELM draws on influential scholars who recognize experience as having a central role in learning and development, most notably John Dewey, Kurt Lewin and Carl Jung. The ELM is based on six propositions drawn from the literature:

1. Learning should be conceived as a process, not in terms of discrete outcomes. Feedback on the effectiveness of an individual's learning efforts is the best way to improve learning.
2. All learning is relearning. Drawing out the beliefs and ideas that a learner already has about a topic enable them to be examined and tested. More refined ideas and knowledge needs to be integrated with existing constructs.
3. Learning requires the resolution of conflicts between dialectically opposed modes of understanding of the world. Kolb describes the learning process as one in which a learner would "move back and forth between opposing modes of reflection and action and feeling and thinking" [35]
4. Learning is a "holistic process of adaptation to the world, since it involves the integrated functioning of the total person" [36], which includes thinking, feeling, perceiving, and behaving.
5. Learning is a result of synergetic transactions between the learner and the environment. According to Piaget [37], learning is the process of assimilating new experiences into existing concepts and projecting existing concepts on to new experiences; and
6. Learning is a social process of creating individual knowledge. Social knowledge is created and recreated through the personal knowledge of individuals.

In his most cited book "Experiential Learning", Kolb [35] maintains that learning is actually one continuous process of knowledge creation, rather than a series of discrete outcomes. It involves transactions between the learner and the environment. Following Dewey's theory [38], Kolb identified four intellectual processes in experiential learning: apprehension versus comprehension and intention versus extension. "Apprehension" is an intellectual process which refers to grasping experience directly. "Comprehension" is a different intellectual process which refers to understanding things indirectly. At the same time, "intention" and "extension" are the intellectual processes of how experience is transformed. "Intention" is a way in which people transform experience through internal reflection. "Extension" is a way in which experience is transformed by actively manipulating the external world Four stages in a learning process are then identified in terms of the four intellectual processes: concrete experience, during which learners rely on their feelings to initialize or motivate learning; reflective observation, during which learners learn by watching others; abstract conceptualization, during which thinking is the main strategy of learning; and active experimentation, during which people learn by doing. Learners go through all four of the learning stages, but each individual learner tends to emphasize one or more of the four modes of the learning process at any given point in their learning activities. This emphasis is known as their learning style [35, 36, 39]. Two dimensions determine each learning style: grasping, which indicates whether learners rely on their feelings or thinking when they learn; and transforming, which indicates whether learners prefer watching other people doing or doing by themselves when they learn.

Each individual can fall into one of the four learning style categories:

- *Divergers*, who grasp experience through apprehension and transform it via intention;
- A*ssimilators*, who grasp experience through comprehension and transform it via intention;

- C*onvergers*, who grasp experience through comprehension and transform it via extension;
- A*ccommodators*, who grasp experience through apprehension and transform it via extension.

Experiential learning theory (ELT) established a learning model from the learners perspective. However, ELT does not take the learning contexts into account –ELT and the LSI are established regardless of the learning materials available and the depth of knowledge studied. In experiential learning theory it remains to be determined whether people would adopt different learning styles when they engage with knowledge at a superficial or deep level, or when they perform learning tasks of different complexity.

When it comes to learning and teaching educational objectives are an important issue to consider, as they best represent how the teacher conceives and strategizes the learning task. Bloom's taxonomy of educational objectives [40] is considered by many educators as a valid benchmark to effectively measure the understanding a student has of a particular subject [41]. It is a hierarchical framework that represents depth of knowledge in the cognitive domain. In Bloom's framework, six levels of cognitive objectives in learning and teaching are identified, namely: knowledge (level 1), comprehension (level 2), application (level 3), analysis (level 4), synthesis (level 5), and evaluation (level 6). Anderson et al. [42] updated and revised Bloom's framework to incorporate recent advancements in cognitive theory. In the revised framework, the cognitive processes remain in six categories, but the two higher level processes (synthesis and evaluation) are revised to evaluation (level 5) and creativity (level 6). Table 1 summarizes the six cognitive levels in the revised framework.

Processes	Sub-processes	Definitions	Examples
Remember	Recognizing Recalling	Retrieve relevant knowledge and/or information from long-term memory.	Recognize the type of a building. Recall the name of a place.
Understand	Interpreting Exemplifying Classifying Summarizing Inferring Comparing Explaining	Construct meanings from given information.	Interpret the meanings of given texts. Give examples of a concept. Put things into categories (e.g. types of buildings, patterns). Compare and explain the difference between two objects.
Apply	Executing Implementing	Carry out a procedure in a given situation	Apply a procedure to a given task.
Analyse	Differentiating Organizing Attributing	Separate given material into its constituent parts. Investigate the inter-relationship between parts and the overall structure or purpose.	Distinguish important elements from unimportant elements of the given task or material. Establish a point of view relative to given material.
Evaluate	Checking Critiquing	Make judgments and critiques based on criteria and standards.	Determine if a conclusion is valid in terms of observed data. Determine if a method is effective.
Create	Generating Planning Producing	Assemble elements to form a new pattern, structure or procedure.	Establish hypotheses. Plan a procedure. Invent a product.

Table 1: The six cognitive levels in the revised framework [42]

It has been suggested that there are similarities between Bloom's taxonomy and Kolb's experiential learning theory. Murphy [43] identifies similarities between the first four levels of Bloom's taxonomy (remember, understand, apply and analyse) and the four dimensions of Kolb's Experiential Learning Model (concrete experience, reflective observation, abstract conceptualization and active experimentation). Howard et al. [41] mapped Bloom's taxonomy onto Kolb's ELM. According to Howard et al. [41], when learning, people usually start with the "why" quadrant, as shown in Figure 1. Then the learning and teaching should move to the "what" quadrant, which represents the first and second level of Bloom's taxonomy (knowledge and comprehension). Learning can then move into the "how" quadrant, which provides students with the challenges of application and analysis. The final move is to the "what if" quadrant, where the last two levels of Bloom's taxonomy are addressed (synthesis and evaluation). Howard et al. [41] suggest that teaching should be organized around this "circle" to accommodate multiple learning styles and to achieve better learning outcomes. Whilst the circle concept appears consistent, Howard et al. [41] did not establish any empirical evidence to support this mapping.

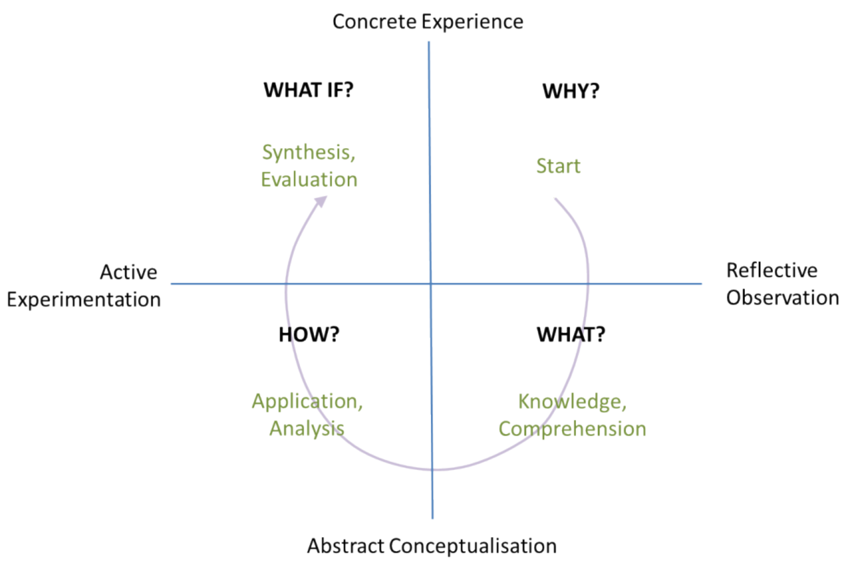


Figure 1: Mapping Bloom's taxonomy onto Kolb's experiential learning model

Jansen [44] conducted a study investigating the relationship between individual learning style and task complexity in the context of online searches. The study posed the research question "are searching characteristics within Anderson et al. [42]'s taxonomy affected by the searcher's learning styles?" Results showed that the learning style of an individual has a significant influence on the how they undertake online searching. However, Jansen [44] did not use Kolb's LSI to identify learning style information. Instead, a questionnaire of their own design is used, containing seven measuring items and using a five-point scale for each item.

Schar et al. [45] conducted a 2x2 between-group experiment to investigate people's preferred interface modes in tasks of different complexity. Recent studies such as Roelle and Berthold [46] investigates the effects of a particular cognitive process (incorporating retrieval) on university students learning and concluded that the complexity of tasks can influence the results. Figl and Recker [47] conducted an empirical study with 120 business students exploring the roles of cognitive style and task complexity preferences in learning, and concluded that the cognitive style and the level of task complexity are relevant predictors for other learning aspects such as user preferences of media formats. In the field of construction higher education, however, no similar study has been established. There is a clear research gap in how the complexity level of learning tasks might affect the way students learn, especially in the digital era.

In summary, Kolb's ELM aims to understand the cognitive learning process from the perspective of a learner, while Bloom's taxonomy of learning objectives aims to provide educators with guidelines and techniques to design effective teaching materials relative to the cognitive domain of the learner. Although Bloom [40]'s taxonomy and Kolb [35]'s ELM contains similarities, there is no substantial theoretical connection between the two models. As discussed earlier, video games have the potential to create virtual world experiences for learning and teaching purposes. Kolb's experiential learning theory explicitly claims that people grasp and transform knowledge through experiences. In construction learning and teaching, experiences of and with the built environment are particularly important and to gain such experiences usually requires the learner to be engaged with the physical environment [48]. In addition, the teaching environment, student expectation and particular teaching technologies have changed massively since Kolb first proposed his ELM and developed LSI Version 1. The significance of technological change has been recognized by some, and de Freitas [49] proposed an adjustment to the ELM to incorporate a further learning style/stage, called exploration, specifically in response to new technology development. However, there have been no corresponding changes to the LSI and there is still a significant lack of empirical evidence specific to the impact that new technologies might have on learning behaviour and preferred learning styles.

3. Research Questions and Experiment Design

The aforementioned discussions provided the main theoretical and methodological grounding for the formulation of our research questions with the aim of drawing conclusions that are of broad relevance to construction educators implementing Virtual learning Environments.

While common sense might suggest that task complexity will influence the individual learning style of students this assertion has not been tested empirically to determine whether any influence is statistically significant, and to what extent task complexity affects the way virtual reality promotes or supports learning styles. To address this potential misunderstanding and other relevant issues, an educational experiment was designed. Kolb's LSI is adopted as the instrument that measures students learning styles (dependent variables), and the level of task complexities are set as the independent variable. It aimed to test the hypothesis:

When using VLEs for construction education, students will adopt different learning styles when engaged in learning tasks of different complexities.

An experimental environment, called The Situation Engine, is set up as a virtual construction site for undergraduate construction students to experience the construction work in progress. The design and development of The Situation Engine draws on powerful pedagogies, including situated learning and experiential learning. It presents near-authentic construction contexts and activities, using those leading-edge immersive techniques that best promote a high level of presence. The experiment was designed to investigate the relationship between task complexity and individual learning styles within the setting of a Virtual Learning Environment in a construction context. In the experiment, each participant is assigned a small learning task and given a short period of time to accomplish the task in The Situation Engine. Figure 2 shows a snapshot from this virtual environment in which the experiment takes place. In the experimental environment, participants can freely navigate around the virtual construction site. Animations such as construction work in progress and directional sounds of the construction site are simulated along with "physical" objects to increase vividness and plausibility. While the participants cannot pick, grab or change the status of the virtual objects in the experiment setting they can walk, jump, climb and collide with virtual terrain, concrete slabs, stairs, sawhorses, stacks of materials and other virtual construction workers. Using these different modes of navigating the site they are in effect collaborating with the site to change their point of view.

Figure 2: The virtual environment designed for the second phase of the experiment

Three construction tasks were designed, based on Bloom's taxonomy of educational objectives [39, 41], and represented three different levels of complexity. The low complexity task only required the cognitive processes of *remembering* and *understanding (one might expect this level of task to be included in the role of Labourer)*. The medium complexity task required the cognitive processes of *applying* and *analysing (one might expect a Tradesperson or Site Supervisor to accommodate this level of task within their responsibilities)*. The high complexity task required the cognitive processes of *evaluating* and *creating (one might expect this level of task to be included in a professional Site Safety Officer role)*. Participants in the experiment were randomly assigned one of the tasks which provided three groups of equal numbers.

Data was collated for each level of complexity and analysed using a between-group method, as shown in Figure 3.

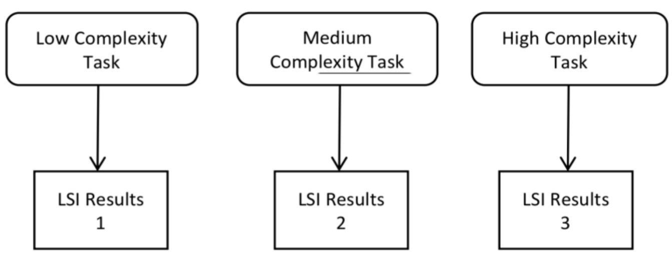


Figure 3: The between-group experiment design

A between-group design was chosen rather than a within-group pattern because it is a cleaner design from a statistical perspective. To undertake a within-group design, each participant would have to undertake all three tasks. Undertaking all three tasks introduces a number of issues, including the potential for learning bias as an individual progress through the tasks; the increased timeframe required overall; and the increased timeframe for individuals, which could have resulted in exhaustion and frustration. An unpaired t-test was used for this analysis since the purpose is to determine if the LSI results were statistically different between any two groups. Each task is described in detail below.

a. The low complexity task

How many rooms can you count?

Instructions

Walk through the house and around the construction site. Your task is to identify and categorise the number of each room type in the house.

Write down the number of each room type in the table below. If you are unsure of the type of a particular room, just categorise it based on your own recollection and understanding of dwellings you have been in previously. The target total number of rooms is given, but there is no absolutely correct answer.

	Total
Living/Lounge Room	
Bedroom	
Kitchen	
Dining Room	
Entrance Foyer	
Bathroom	
Garage	
Laundry	
Study Room	
Storage	
Target Total of Rooms	**15**

You have five minutes to complete the exercise. **Please work independently and do not seek assistance** – just give it your best shot!

Each participant received a task sheet as shown in Figure 4, which presents the instructions of the low complexity task. Participants assigned to the low complexity task needed to explore the virtual construction site, identify, categories and count the number of particular types of room in the house under construction. They were asked to write down the number of each type of room in a table listed on the task sheet. This task only required participants to learn the very basic aspects of the virtual environment and perform a task based on their prior knowledge and memory. Participants were expected to mainly explore the indoor space of the construction site. Figure 4 (b) illustrates the scenes that participants undertaking this task might encounter.

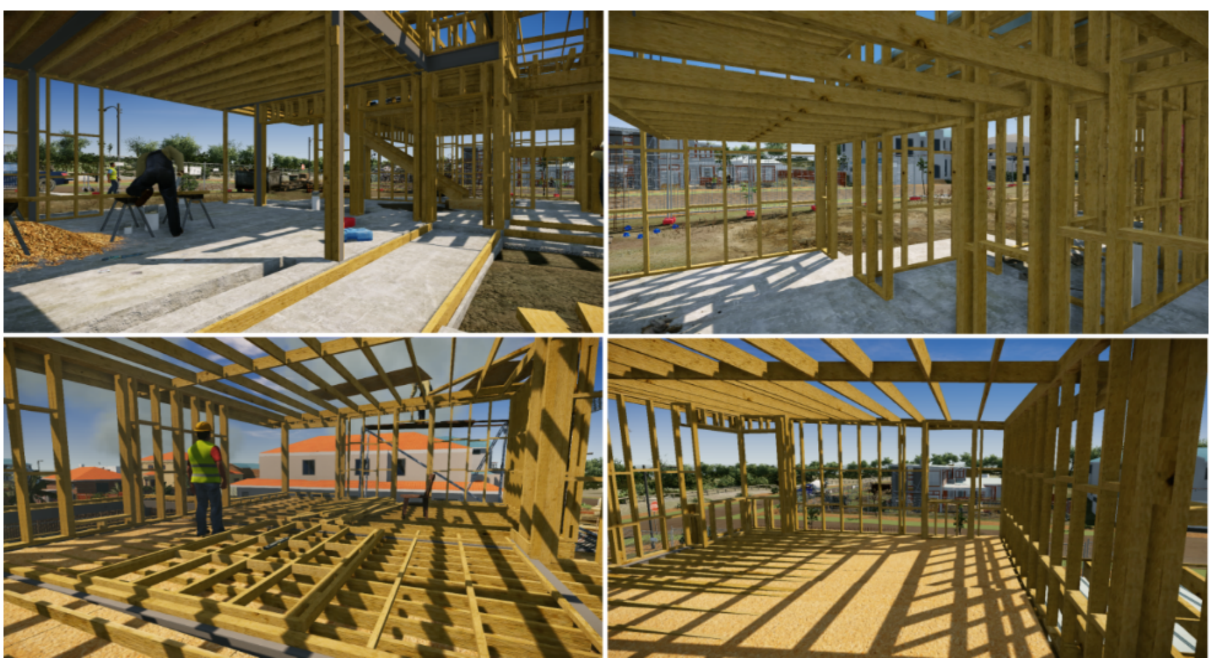
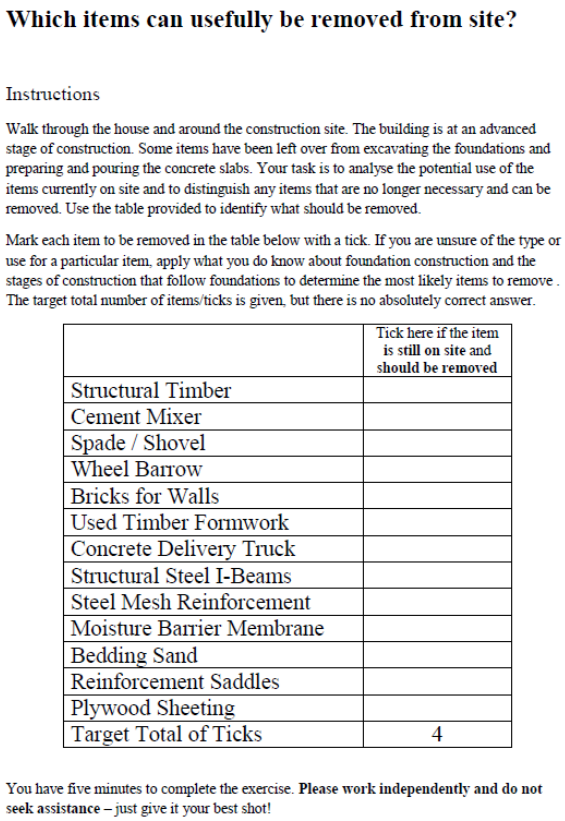


Figure 4: Low Complexity task and scenes that could be encountered in this task.

b. The medium complexity task

Participants assigned to the medium complexity task received a task sheet as shown in Figure 5. They were advised that the building was at an advanced stage of construction; however, some items had been left over from excavating the foundations and preparing and pouring the concrete slabs. Participants assigned to this task were asked to analyse the potential use of the items currently on site, and to distinguish any items that are no longer necessary and could be removed. They were asked to identify the four items that should be removed and note them in the task sheet table.

Participants undertaking this task needed to analyse the situation, grasp the information provided both by the virtual environment and the task sheet, and then apply the information to accomplish the learning task. They were expected to be viewing scenes such as those shown in Figure 5.



Which items can usefully be removed from site?

Instructions

Walk through the house and around the construction site. The building is at an advanced stage of construction. Some items have been left over from excavating the foundations and preparing and pouring the concrete slabs. Your task is to analyse the potential use of the items currently on site and to distinguish any items that are no longer necessary and can be removed. Use the table provided to identify what should be removed.

Mark each item to be removed in the table below with a tick. If you are unsure of the type or use for a particular item, apply what you do know about foundation construction and the stages of construction that follow foundations to determine the most likely items to remove . The target total number of items/ticks is given, but there is no absolutely correct answer.

	Tick here if the item is still on site and **should be removed**
Structural Timber	
Cement Mixer	
Spade / Shovel	
Wheel Barrow	
Bricks for Walls	
Used Timber Formwork	
Concrete Delivery Truck	
Structural Steel I-Beams	
Steel Mesh Reinforcement	
Moisture Barrier Membrane	
Bedding Sand	
Reinforcement Saddles	
Plywood Sheeting	
Target Total of Ticks	4

You have five minutes to complete the exercise. **Please work independently and do not seek assistance** – just give it your best shot!

Figure 5: Medium complexity task and scenes that may be seen in this task

c. The high complexity task

How can you best improve safety on this site?

Instructions

Walk through the house and around the construction site. There are a number of things on site that represent serious dangers to the health and safety of the workers. Imagine you are the project manager. Your task is to evaluate the potential dangers actually present on the site and to create a procedure (in other words, a series of steps) that will provide the maximum safety improvement in the minimum number of steps. Please write down your procedure below.

Remember, the goal is to create the maximum safety improvement for the minimum number of steps. The target total number of steps is **no more than 4**, and there is no absolutely correct answer.

1.

2.

3.

4.

You have five minutes to complete the exercise. **Please work independently and do not seek assistance** – just give it your best shot!

Participants assigned to the high complexity task were given a task sheet as shown in Figure 6. They were asked to identify and evaluate elements of the virtual construction site that represent potential dangers to the health and safety of the workers. They also needed to create a procedure (a series of steps) that would result in the greatest safety improvement on that site. They were encouraged to use the minimum number of steps and were asked to write down the procedure on the task sheet in short sentences.

The potential dangers on the site included timber being placed on uneven ground; the impact of running water from a nearby water tap; an exposed pipe in a large excavation hole with no barriers in place; workers on site not wearing the required safety helmet; and the lack of barrier protection on the upper floor of the building. Participants undertaking this task were expected to pay particular attention to a series of scenes as shown in Figure 6.

Figure 6: High complexity task and scenes that may be seen in this task

Immediately after the virtual learning session, the students were asked to fill in a learning style inventory (LSI) survey. Each item in the LSI took the form of a sentence beginning with a choice of four endings. Each ending to each sentence represented only one of the four modes. For example, the sentence beginning "When I learn…" might have the following choice of endings to rank: "… I like to deal with my feelings.", Concrete Experience (CE); "… I like to watch and listen.", Reflective Observation (RO); "… I like to think about ideas.", Abstract Conceptualization (AC); "… I like to be doing things.", Active Experimentation (AE). Respondents were required to rank the endings for each sentence based on how well they think each one described how they prefer to learn. The ranking starts with a "4" for the ending that best accorded with their learning preference, down to a "1" for the ending that accorded the least. All endings had to be ranked, and all had to be ranked differently. To determine the learning style preference, a total score had been calculated for all designated CE, RO, AC, and AE endings. Where a given mode is ranked highest for every item, the maximum score is $12 \times 4 = 48$. The minimum score for any mode is $12 \times 1 = 12$. The overall score should always be $12 \times (4 + 3 + 2 + 1) = 120$. Once all four totals were calculated a location along each of the two dimensions was determined by calculating a balance-point between each score on that dimension. For example, the result of [AC – CE] provided a position on the grasping (comprehension/apprehension) dimension; which is referred as the AC-CE result by Kolb. The result of (AE – RO) provided a position on the transformation (extension/intention) dimension.

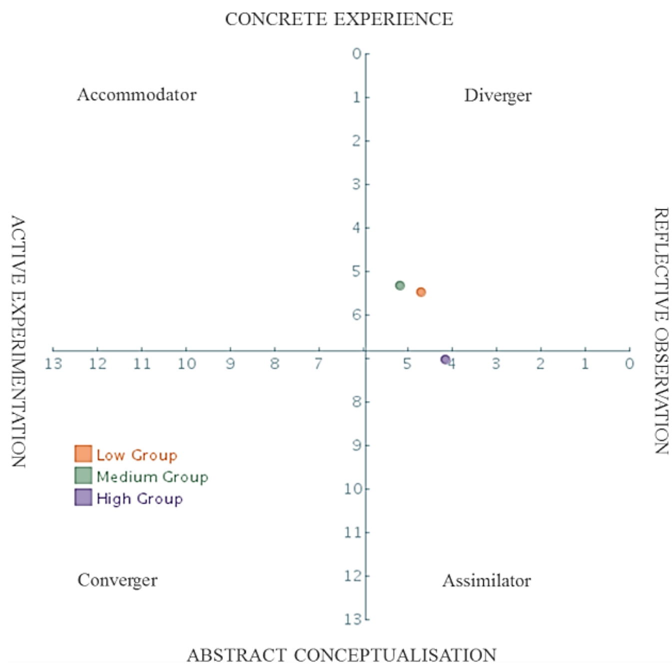
4. Results and Analysis

The experiment involved students who were enrolled in the undergraduate courses in the Faculty of Built Environment, at the University of New South Wales, Australia. 253 undergraduate students participated in the study and were invited to the lab in groups of six. Due to incomplete questionnaires, especially the LSI survey, some of the responses were counted as invalid. The number of valid responses from task one was 78 (6 invalid entries), from task two was 76 (8 invalid entries) and from task three was 74 (11 invalid entries). The 228 valid responses were analysed following the calculation guidelines for the LSI. A score for each learning style dimension (CE, RO, AC, AE, AC-CE and AE-RO) is calculated for each participant. Table 2 summarises the mean values for the six learning style dimensions for each task complexity group. The results show that the average CE score declines slightly as the task complexity increases. There is no consistent trend in other dimensions and the differences between each group pairing are relatively very small. The AC-CE score of the high group does appear to be distinctly higher than those of the low group and the medium group however the result is not statistically significant.

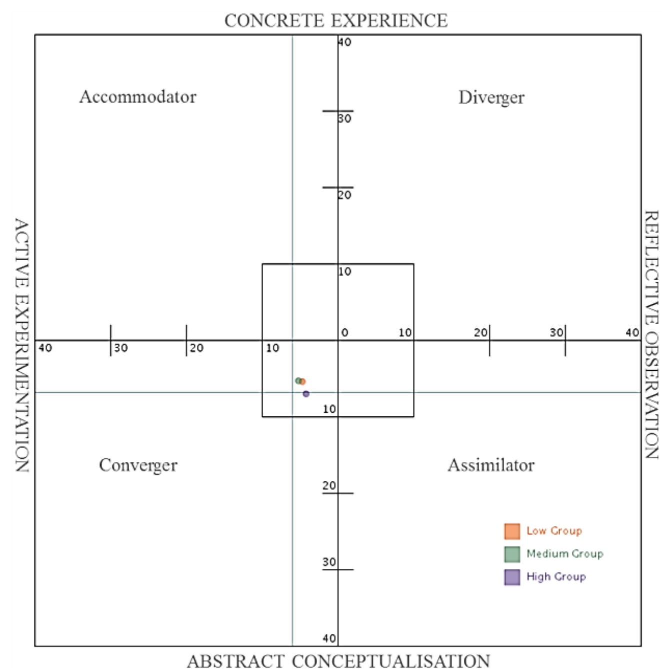
Task Complexity Groups	N		CE	RO	AC	AE	AC-CE	AE-RO
Low Group	78	Mean	25.60	29.55	31.08	34.24	5.47	4.69
		S.D.	5.78	6.16	5.37	6.64	9.29	11.16
Medium Group	76	Mean	25.36	29.47	30.70	34.64	5.34	5.17
		S.D.	6.63	6.18	6.37	6.27	11.15	10.58
High Group	74	Mean	24.57	29.86	31.61	34.00	7.04	4.14
		S.D.	6.43	6.64	5.46	6.31	9.78	10.99

Table 2: LSI results from different task complexity groups

Figure 7 illustrates the LSI "balance points" of the three task complexity groups based on the average AC-CE and AE-RO scores. The balance points were calculated by the LSI results from more than seven thousand participants in Kolb's study [35]. The grid shown in (a) only covers a small region of the LSI grid while (b) shows the actual LSI grid. The LSI balance points of the low group and the medium group are located in the "diverger" quadrant. The LSI balance point of the high group falls into the "assimilator" quadrant, but it is very close to the diverger-assimilator boundary. The LSI balance points of the low group and the medium group appear to be very close to each other and in (b) they almost coincide.



(a)



(b)

Figure 7: LSI balance points of the task complexity groups (a) in the zoom-in region and (b) on the original LSI grid

Table 3 shows the number of participants for each learning style in each of the three task complexity groups. Across the 228 valid entries, 78 participants are in the low group, 76 are in the medium group and 74 are in the high group, demonstrating an even balance for each category.

Task Groups	Diverger		Assimilator		Converger		Accommodator		Total
Low Group (Task 1)	20	25.64%	23	29.49%	20	25.61%	15	19.23%	78
Medium Group (Task 2)	19	25.00%	18	23.68%	16	21.05%	23	30.26%	76
High Group (Task 3)	13	17.57%	26	35.14%	17	22.97%	18	24.32%	74
Total	**52**	**22.81%**	**67**	**29.39%**	**53**	**23.24%**	**56**	**24.56%**	**228**

Table 3 Number of participants with different learning styles in task complexity groups

Figure 8 illustrates the proportions of the four learning styles in each task complexity group. The proportion of each colour on the charts in Figure 8 represents the portion of different learning styles in each of the three task complexity groups. The locations of the learning styles on the charts match the locations of the four learning styles on Kolb's LSI grid.

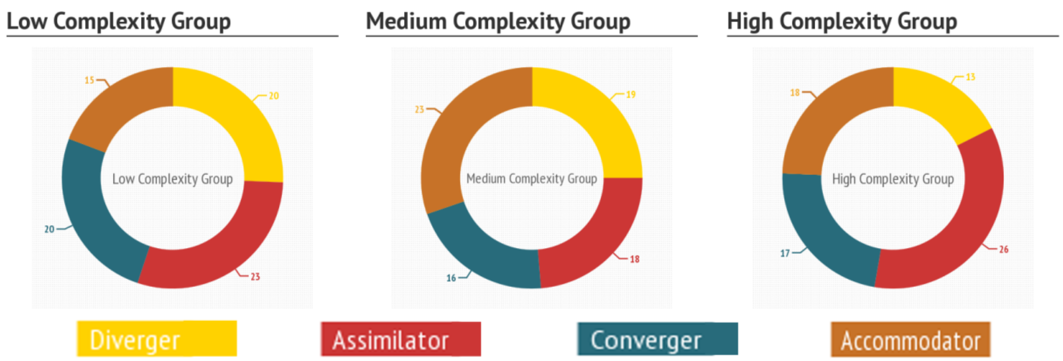


Figure 8: Proportions of four learning styles in each task group

Table 3 and Figure 8 show that there is a slight imbalance in the proportions for each task complexity group. In the low group, in which the participants were assigned a task with a lower level of complexity (identifying and categorising rooms of different types), the "accommodator" learning style is least represented and the "assimilator" is most popular. In the medium group in which the participants were assigned a task with a medium level of complexity (analysing a current construction situation and identifying items that should be removed), "converger" is least represented and "accommodator" the most. In the high group in which the participants were assigned a task with a high level of complexity (evaluating hazards and creating a procedure to improve safety), the "diverger" learning style is the least preferred and the "assimilator" is the most.

The result indicates that for the low task complexity group participants did prefer the "assimilator" learning style, as predicted in the theoretical relationship between Kolb and Bloom. However, neither the medium complexity group nor the high complexity group conform to the theoretical relationship of "convergers" and "accommodator" learning styles respectively. In fact, the "converger" learning style is the least represented in the medium complexity task group. The highest proportion of learning styles for the high complexity task group was actually achieved by the "assimilator".

It should also be noted that for several of the task complexity groups the group LSI balance point does not lie within the same learning style quadrant as the largest proportion of individuals in that group. For instance, the LSI balance points of both the low task complexity group and the medium task complexity group are in the "diverger" quadrant. But the major number of low task complexity members favoured "assimilator" and the major proportion of medium task complexity members favoured "accommodator".

Figure 9 shows the distributions of the CE/RO/AC/AE scores in each task complexity group. From the graphs it is apparent that the distributions do not strictly follow a "bell-curve". Some of the curves are skewed (such as CE in the low task complexity group) and some are bimodal (such as CE in the medium task complexity group).

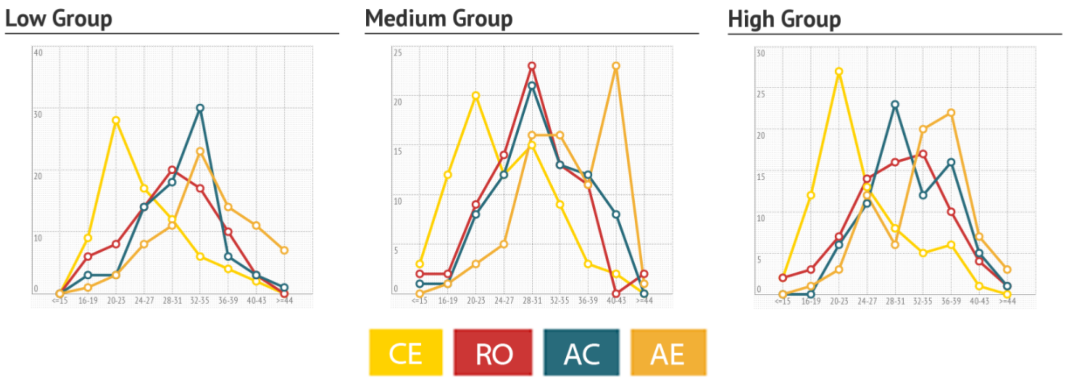


Figure 9: Distribution of CE/RO/AC/AE scores in each task complexity group

Figure 10 shows the distributions of participants in the AC-CE and AE-RO dimensions. The distributions do not follow a bell-shaped curve either, which means the scores are not normally distributed. In general, the curves in Figure 10 appear to be bimodal or multimodal.

Figure 10: Distribution of AC-CE/AE-RO scores in each task complexity group

T-tests were applied to the LSI results reported by the three groups of participants, who performed on the three tasks of different levels of complexity. The tests investigate the differences between each pair of the task complexity groups (Low vs. Medium, Low vs. High, and Medium vs. High). The results are shown in Figure 11. The results indicate that no significant difference is found in any dimension between any two groups. In other words, people assigned to tasks with different levels of complexity do not demonstrate different learning styles to any significant extent.

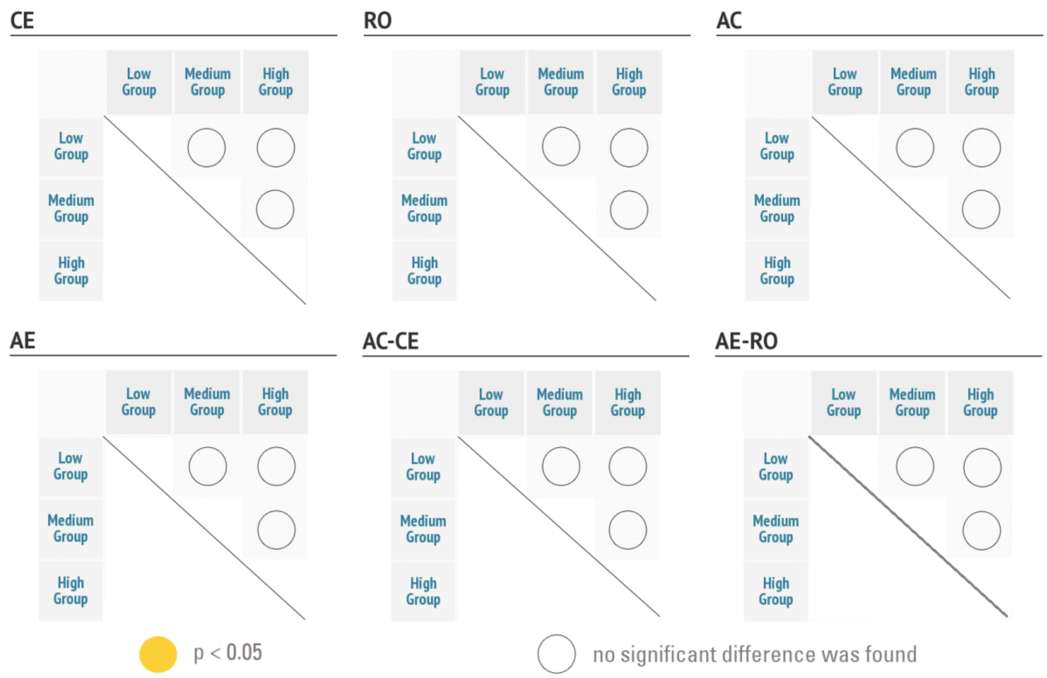


Figure 11: t-test results in each LSI dimension between task complexity groups

5. Conclusions and Implications

The literature in technology mediated learning indicates that task complexity promotes particular learning styles and/or influence the dynamics of learning styles for a group of people. This paper investigated whether task complexity had any influence on an individuals preferred learning style when learning using virtual reality technology in construction higher education.

From the analysis of data collected, no significant difference could be identified among groups that were assigned tasks of different levels of complexity. This was the case in terms of the average scores of each group's LSI result and in the spread of the individuals within those groups. It was concluded, therefore, that when people learn with virtual reality technology there is no evidence to suggest the level of task complexity has any influence on learning styles. Task complexity does not change the average learning style for a group, thus the hypothesis "When using VLEs for construction education, students will adopt different learning styles when engaged in learning tasks of different complexities" is rejected.

6. Limitations and Future Work

While offering very exciting opportunities VR technology has yet to realise a great deal of its early potential. At the time of this research a complete, hyper-immersive VR environment was not achievable at an affordable cost. Low-cost VR devices are still at an experimental stage and cannot yet deliver a fully immersive experience. For instance, people are experiencing serious motion sickness problems with the Oculus Rift and there are tracking accuracy problems with fine motor movements. These technological limits restrict how people engage, interact and experience VR environments, and represent a major barrier to the user's sense of presence [50].

In this research, whilst the functionality of The Situation Engine is advanced, a number of potential extensions to the hyper-immersive qualities of the technology (devices such as HMDs and motion trackers) have been tested but not adopted due to the immaturity of the technology. Participants in the research were only tested in one experimental setting. The approach worked well and enabled a large number of participants to be processed. However, the introduction of more hyper-immersive technologies could certainly change the overall sense of presence and thereby impact the results. Furthermore, the impact of additional physiological factors (such as natural head and body movements) on the effectiveness of VLEs should be investigated.

References

[1] M. Townsend and R. Weerasuriya, Beyond blue to green: the benefits of contact with nature for mental health and well-being, Beyond Blue Limited: Melbourne, Australia, 2010, ISBN: 978-0-9581971-6-8, https://www.deakin.edu.au/__data/assets/pdf_file/0004/310747/Beyond-Blue-To-Green-Literature-Review.pdf, Accessed date: 17 Feb 2020.

[2] C. Dede, The evolution of constructivist learning environments: immersion in distributed, virtual worlds. Educational Technology, 35 (5) (1995) 46-52. https://www.jstor.org/stable/44428298, Accessed date: 17 Feb 2020.

[3] B. Dalgarno, M. Lee, L. Carlson, S. Gregory and B. Tynan, An Australian and New Zealand scoping study on the use of 3D immersive virtual worlds in higher education. Australasian Journal of Educational Technology, 27(1) (2011) 1-15, https://doi.org/10.14742/ajet.978

[4] W. Yan, C. Culp, and R. Graf, Integrating BIM and gaming for real-time interactive architectural visualization. Automation in Construction, 20(4) (2011) 446-458, https://doi.org/10.1016/j.autcon.2010.11.013

[5] A. Margaryan, A. Littlejohn and G. Vojt, Are digital natives a myth or reality? University students' use of digital technologies, Computers & Education, 56 (2) (2011) 429-440, https://doi.org/10.1016/j.compedu.2010.09.004

[6] L. Starkey, Evaluating learning in the 21st century: a digital age learning matrix, Technology, Pedagogy and Education, 20(1) (2011) 19-39, https://doi.org/10.1080/1475939X.2011.554021

[7] C. Riener and D. Willingham, the myth of learning styles, change: The Magazine of Higher Learning, 42(5) (2010), 32-35, https://doi.org/10.1080/00091383.2010.503139

[8] T. Kocaturk, A socio-cognitive approach to knowledge construction through blended learning, Journal of Problem Based Learning in Higher Education, 5(1) (2017) 1-21, https://doi.org/10.1016/j.compedu.2010.07.017

[9] F. Romanelli, E. Bird and M. Ryan, Learning styles: a review of theory, application and best practices, American Journal of Pharmaceutical Education, 73(1) (2009) 1-5, https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2690881/, Accessed date: 17 Feb 2020.

[10] R. Bartle, What are virtual worlds? Excerpted from designing virtual worlds, New Riders Publishing, 2003, ISBN: 0-7357-1351-0, http://www.peachpit.com/articles/article.aspx?p=99703 Accessed date: 18 Feb 2020.

[11] L. Robert, Adaptive Behavior and Economic Theory, the Journal of Business, 59 (4) (1986), S401-S426, https://www.jstor.org/stable/2352771, Accessed date: 18 Feb 2020.

[12] A. Cram, R. Lowe and K. Lumkin, Assessing spatial design in virtual environments, in S. Kennedy-Clark, K. Everett and P. Wheeler (Eds.), Cases on the Assessment of Scenario and Game-Based Virtual Worlds in Higher Education. IGI Global, pp74-123, 2014, ISBN: 9781466644700, https://www.igi-global.com/gateway/chapter/109265, Accessed date: 18 Feb 2020.

[13] F. Laamarti, M. Eid and A. El Saddik, An overview of serious games. International Journal of Computer Games Technology, (2014), https://doi.org/10.1155/2014/358152

[14] S. Newton and R. Lowe, Situational eLearning with immersive technologies. In S. Saha, Y. Zhang, S. Yazdani and A. Singh (Eds.), Implementing Innovative Ideas in Structural Engineering and Project Management, ISEC Press, 2015, pp.3-12, ISBN: 978-0-9960437-1-7, https://www.isec-society.org/ISEC_PRESS/ISEC_08/pdf/EPE-14_v4_444.pdf, Accessed date: 18 Feb 2020.

[15] S. Newton, R. Lowe, S. Rowlinson and D. H. T. Walker, (2020). The new role for emerging digital technology to facilitate IPD and improve collaboration: a disruptive innovation perspective. In D. Walker and S. Rowlinson (Eds.) Routledge Handbook of Integrated Project Delivery. Routledge, London, 2020, pp. 347-364, ISBN 9781138736689, https://trove.nla.gov.au/work/236802383, Accessed date: 18 Feb 2020.

[16] A. E. Afrooz, R. Lowe, C. Pettit, S. Leo, 3D and virtual reality for supporting redevelopment assessment. In R. Reed, C. Pettit (Eds.) Real Estate and GIS: the Application of Mapping Technologies, Routledge, London, 2019, pp. 162-185, ISBN: 9781315642789, https://doi.org/10.1201/9781315642789

[17] J. Mitchell and R. Lowe, Simulation of clinical work environments using BIM and computer gaming Technology. Asia Pacific Journal of Health Management, 5(1) (2010) 31-39, ISSN: 1833-3818. https://search.informit.com.au/documentSummary;dn=450713923378620;res=IELAPA Accessed date: 18 Feb 2020.

[18] P. Milgram, F.A. Kishino, Taxonomy of mixed reality visual-displays, IEICE TRANSACTIONS on Information and Systems, 77 (12) (1994), pp.1321-1329, ISSN: 0916-8532, http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.102.4646&rep=rep1&type=pdf, Accessed date: 18 Feb 2020.

[19] E.Z. Barsom, M. Graafland and M.P. Schijven, Systematic review on the effectiveness of augmented reality applications in medical training, Surgical Endoscopy 30 (10) (2016), pp.4174-4183, https://doi.org/10.1007/s00464-016-4800-6

[20] J. N. Silva, M. Southworth, C. Raptis and J. Silva, Emerging applications of virtual reality in cardiovascular medicine, JACC: Basic to Translational Science, 3(3) (2018), pp. 420-430. https://doi.org/10.1016/j.jacbts.2017.11.009

[21] G. R. Norman, L. E. M. Grierson, J. Sherbino, S. J. Hamstra, H. G. Schmidt and S. Mamede, Expertise in medicine and surgery, In K. Ericsson, R. Hoffman, A. Kozbelt and A. Williams (Eds.), The Cambridge Handbook of Expertise and Expert Performance (Cambridge Handbooks in Psychology). Cambridge: Cambridge University Press, 2018, pp. 331-355, ISBN: 9781316480748, https://doi.org/10.1017/9781316480748.019

[22] J. Steuer, Defining virtual reality: dimensions determining telepresence, Journal of Communication, 42(4) (1992), pp. 73-93, https://doi.org/10.1111/j.1460-2466.1992.tb00812.x

[23] C. C. Abt, Serious Games. New York: Viking Press, 1970, ISBN: 0-8191-6147-0, https://books.google.com/books?id=axUs9HA-hF8C Accessed date: 19 Feb 2020.

[24] D. Di Mascio and R. Dalton, Using serious games to establish a dialogue between designers and citizens in participatory design, In M. Ma and A. Oikonomou (Eds.) Serious Games and Edutainment Applications, Springer, Cham, 2017, pp. 433–454, ISBN: 9783319516455, https://doi.org/10.1007/978-3-319-51645-5_20

[25] B. Stokes, Video games have changed: time to consider "serious games"?, Development Education Journal, 11(3) (2005), pp. 12-19, http://benjaminstokes.net/doc/Stokes(2005)--Videogames-have-changed-time-to-consider-Serious-Games.pdf, Accessed date: 19 Feb 2020.

[26] F. Ulrich and N. Henrik-Helms, Creating evaluation profiles for games designed to be fun: an interpretive framework for serious game mechanics, Simulation & Gaming 48 (5) (2017), pp. 695-714, https://doi.org/10.1177/1046878117709841

[27] Arnab, S., S. de Freitas, F. Bellott, T. Lim, S. Louchart, N. Suttie, A. De Gloria, Mapping learning and game mechanics for serious games analysis, British Journal of Educational Technology, 46(2) (2015), pp. 391–411, https://doi.org/10.1111/bjet.12113

[28] S. Corrigan, G. D. R. Zon, A. Maij, N. McDonald and L. Mårtensson, An approach to collaborative learning and the serious game development, Cognition, Technology & Work, 17(2) (2015), pp. 269–278, https://doi.org/10.1007/s10111-014-0289-8

[29] M. Kebritchi and A. Hirumi, Examining the pedagogical foundations of modern educational computer games, Computers and Education, 51(4) (2008), pp. 1729–1743, https://doi.org/10.1016/j.compedu.2008.05.004

[30] N. Nazry and D. Romano, Mood and learning in navigation-based serious games, Computers in Human Behavior, 73(1) (2017), pp. 596–604, https://doi.org/10.1016/j.chb.2017.03.040

[31] P. Rooney, A theoretical framework for serious game design: exploring pedagogy, play and fidelity and their implications for the design process, International Journal of Game-Based Learning, 2(4) (2012), pp. 41–60, https://doi.org/10.4018/ijgbl.2012100103

[32] L. Jarmon, T. Traphagan, M. Mayrath and A. Trivedi, Virtual world teaching, experiential learning, and assessment: an interdisciplinary communication course in Second Life. Computers & Education, 53(1) (2009), pp. 169-182, https://doi.org/10.1016/j.compedu.2009.01.010

[33] F. Carter, M. Schijven, R. Aggarwal, T. Grantcharov, N. Francis, G. Hanna and J. Jakimowicz, Consensus guidelines for validation of virtual reality surgical simulators. Surgical Endoscopy and Other Interventional Techniques, 19(12) (2005), pp. 1523-1532, https://doi.org/10.1007/978-3-319-51645-5_20

[34] D. Kolb and M. Goldman, Toward a typology of learning styles and learning environments: an investigation of the impact of learning styles and discipline demands on the academic performance, social adaptation and career choices of MIT seniors, Cambridge, Massachusetts, 1973, ISBN: 0343298384, http://hdl.handle.net/1721.1/49235 Accessed date: 19 Feb 2020.

[35] D. Kolb, Experiential learning: experience as the source of learning and development, Prentice-Hall, New Jersey, 1984, ISBN: 0133892409, http://www.learningfromexperience.com/images/uploads/process-of-experiential-learning.pdf Accessed date: 19 Feb 2020.

[36] A. Kolb and D. Kolb, Learning styles and learning spaces: enhancing experiential learning in higher education, Academy of Management Learning & Education, 4(2) (2005), pp. 193-212, https://doi.org/10.5465/amle.2005.17268566

[37] J. Piaget, The psychology of intelligence, Routledge and Paul, 1950, ISBN: 0415-21006-2, https://content.taylorfrancis.com/books/download?dac=C2004-0-01022-1&isbn=9781134617791&format=googlePreviewPdf Accessed date: 19 Feb 2020

[38] J. Dewey, Experience and nature, Vol. 471. Courier Corporation, 1958, ISBN: 1446547825, https://books.google.com.au/books?id=P6a_Jd2OxpsC Accessed date: 19 Feb 2020

[39] D. A. Kolb, R. E. Boyatzis and C. Mainemelis, Experiential learning theory: Previous research and new directions, In R. J. Sternberg and L. Zhang (Eds.) Perspectives on Thinking, Learning, and Cognitive Styles, 2001, ISBN: 9781410605986, pp. 227-247, https://doi.org/10.4324/9781410605986-9

[40] B. S. Bloom, Taxonomy of educational objectives: the classification of educational goals. In B. S. Bloom (Eds.) Handbook I: Cognitive domain, McKay, London, 1956, ISBN: 0582280109, https://trove.nla.gov.au/version/28325934 Accessed date: 19 Feb 2020

[41] R. A. Howard, C. A. Carver and W. D. Lane, Felder's learning styles, Bloom's taxonomy, and the Kolb learning cycle: tying it all together in the CS2 course. ACM SIGCSE Bulletin, 28(1) (1996), pp. 227-231, https://doi.org/10.1145/236452.236545

[42] L. W. Anderson, D. R. Krathwohl and B. S. Bloom, A taxonomy for learning, teaching, and assessing: A revision of Bloom's taxonomy of educational objectives. Longman, New York, 2001, ISBN: 0321084055, https://trove.nla.gov.au/version/40563384 Access date: 19 Feb 2020.

[43] E. Murphy, Prior Learning Assessment: A Review of Bloom's Taxonomy and Kolb's Theory of Experiential Learning: Practical Uses for Prior Learning Assessment, The Journal of Continuing Higher Educati*on*, 55(3) (2007), pp. 64-66, https://doi.org/10.1080/07377366.2007.10400135

[44] B. Jansen, D. Booth and B. Smith, Using the taxonomy of cognitive learning to model online searching. Information Processing & Management, 45(6) (2009), pp. 643-663, https://doi.org/10.1016/j.ipm.2009.05.004

[45] S. G. Schar, C. Schierz, F. Stoll and H. Krueger, The effect of the interface on learning style in a simulation-based learning situation, International Journal of Human-Computer Interaction, 9(3) (1997), pp. 235-253, https://doi.org/10.1207/s15327590ijhc0903_3

[46] J. Roelle and K. Berthold, Effects of incorporating retrieval into learning tasks: the complexity of the tasks matters. Learning and Instruction, 49 (2017), pp. 142-156, https://doi.org/10.1016/j.learninstruc.2017.01.008

[47] K. Figl and J. Recker, Exploring cognitive style and task-specific preferences for process representations, Requirements Engineering, 21(1) (2016), pp. 63-85, https://doi.org/10.1007/s00766-014-0210-2

[48] Y. Chee, Embodiment, embeddedness, and experience: game-based learning and the construction of identity. Research and Practice in Technology Enhanced Learning, 2(01) (2007), pp. 3-30, https://doi.org/10.1142/S1793206807000282

[49] S. de Freitas and T. Neumann, The use of 'exploratory learning' for supporting immersive learning in virtual environments, Computers & Education, 52(2) (2009), pp. 343-352, https://doi.org/10.1016/j.compedu.2008.09.010

[50] R. Wang, S. Newton and R. Lowe, Experiential learning styles in the age of a virtual surrogate, International Journal of Architectural Research: ArchNet-IJAR, 9(3) (2015), pp. 93-110, https://archnet.org/publications/10418 Accessed date: 19 Feb 2020.