The Effects of Cognitive Load on Engagement in a Virtual Reality Learning Environment

Jhon Alexander Bueno-Vesga* Xinhao Xu† Hao He‡

School of Information Science and Learning Technologies, University of Missouri, Columbia, USA

Abstract

Engagement has been traditionally linked to presence in desktop-based virtual reality learning environments. Although several studies have been performed to determine other factors affecting cognitive engagement, the role of cognitive load as a factor of student's engagement in desktop-based virtual reality (VR) has received little attention in the literature. The main purpose of this study was to explain if individual dimensions of cognitive load (mental demand, effort, and frustration level) can be used in addition to factors like presence and self-efficacy to predict student's cognitive engagement. The results of the study confirmed presence and self-efficacy as significant predictors of student's engagement. Also, a three-step hierarchical regression analysis revealed that two of the three individual dimensions of cognitive load (effort and frustration level) were also significant predictors of student's engagement.

Keywords: Virtual Reality, Cognitive Engagement, Presence, Self-efficacy, Cognitive Load, Effort, Frustration.

Index Terms: [Human-centered Computing]: Interaction Paradigms: Virtual Reality; [Human-centered Computing]: Virtual Reality; [Human-centered Computing]: User studies

1 Introduction

Engagement has been highlighted by the literature as "critical to learning" [35, pp. 131]. One of its facets, cognitive engagement, refers to the level of involvement of the student with the learning experience to a point that they are willing to invest the necessary effort "to comprehend complex ideas and master difficult skills" [14, pp. 60]. Engagement also involves "self-regulating his or her actions, and exhibiting academic strategies" [35, pp. 123]. One of the reasons making engagement a desirable outcome is that it is presumed to be malleable [14]; this means that it can happen as a result of the interactions with the learning environment or the characteristics of it [35]. This is important because it implies that changes in the learning environment and the conditions of the elements related to it can be done to increase student engagement.

Of the types of engagement, the one that may have received more attention in academia is cognitive engagement. Marks [25, pp. 154-155] defined it as "a psychological process involving the attention, interest, investment, and effort students expend in the work of learning". He pointed out that cognitive engagement can change in different educational experiences.

A lot has been said about cognitive engagement in desktop-based virtual learning environments. This might be because of empirical evidence found about its influence on student's academic achievement [16]. Smiley and Anderson [34] emphasized that it is important to study cognitive engagement so proper decisions are made to reduce the likelihood of students becoming bored and uninvolved. By understanding factors driving student's cognitive engagement, educators can proactively try to implement practical interventions or make modifications that can potentially increase it.

Several factors affecting cognitive engagement have been identified in the literature. A study of online multiuser virtual environments showed that presence is a significant predictor of student's engagement [9]. Self-efficacy has also been found as significant in the context of virtual worlds with students [29] and pre-service teachers [27].

Cognitive load is also considered a promising factor of student's engagement in the context of virtual reality. Although early studies found an association between cognitive load and engagement [6, 17], this association in the context of virtual reality has received little attention in the literature. We explored this association utilizing an innovative approach. We did not use cognitive load as a global score but as the multidimensional construct it is, as indicated in [15] and confirmed by several other studies [26, 30, 38, 46].

Thus, the purpose of this study was to investigate if presence, self-efficacy, and individual dimensions of cognitive load could be important predictors of engagement in virtual reality learning environments. For the analysis, we measured three dimensions of cognitive load: mental demand, effort, and frustration level. We incorporated them into our predictive model using hierarchical regression analysis.

For our data collection, we surveyed a group of online students participating in a newly implemented virtual reality module of a digital media course offered by a land-grant university in the US. Cognitive engagement, presence, self-efficacy, and three dimensions of cognitive load (mental demand, effort, and frustration level) were part of the survey.

We used OpenSimulator [47], an open-source 3D virtual reality engine, to build a 3D VR learning environment for the experiment. Given that the participants were online students with often limited resources, we chose this platform because it provides a 3D virtual reality experience, but it does not require students to have any additional hardware or high-performance computational equipment.

2 Theory

2.1 Cognitive Engagement in VR environments

Student's engagement in higher education has been a prevalent topic for the educational research community. This is because of its association with desirable learning outcomes like critical thinking and grades [8], educational quality [31], and also with indicators of student success like student academic performance [4].

A handful of studies related to cognitive engagement in the context of virtual reality have been published recently. An empirical study [9] found that student engagement was significantly higher in a virtual reality learning environment than in a traditional asynchronous learning platform. The author concluded

*e-mail:jab55d@umsystem.edu
†e-mail:xuxinhao@missouri.edu
‡e-mail:hhv5b@umsystem.edu

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that increased student engagement in VR platforms can potentially enhance learning outcomes. In a similar study, Brondi *et al*. [7] assessed the impact of immersive VR technologies on engagement and presence. They tested subjects of a group playing a collaborative game in a VR environment with several configurations, offering different levels of immersion. They found that highly immersive VR environments offer a higher level of engagement. This is in agreement with the findings of later studies [1, 22] showing higher levels of engagement in students using immersive VR experiences (like those using head-mounted devices) compared to those using a classical non-VR environment.

2.2 Presence and Engagement

Presence is defined as the sensation of "being there" [12, pp. 1116], a sensation exclusive of online environments causing users to feel like they are in a parallel space mediated by a computer. In their study, they reported that presence is experienced in 3D virtual reality learning environments (VRLE). Furthermore, Claman [9] found that students using a VRLE reported higher levels of presence compared to those using a traditional asynchronous learning system. Franceschi, *et al.* [13] also found associations between presence and student engagement when using 3D VRLEs. Additionally, Claman [9] identified cognitive presence as the main factor explaining an increase in engagement when students receive instruction in a multiuser virtual reality environment compared to those students using a learning management system.

This study expected presence to show a positive influence on the student's engagement when using VR. Thus, the resulting hypothesis is:

H1: Presence will have a significant positive influence on the student's cognitive engagement when interacting with a VR learning environment.

2.3 Self-efficacy and Engagement

Computer self-efficacy "represents one's belief about her/his ability to perform a specific task/job using a computer" [33, pp. 226]. It does not refer to the actual skills that users have, but instead, it shows their own "judgments of their capabilities to organize and execute courses of action required to attaining designated types of performance" [3, pp. 391].

In the specific area of VR, Pellas [29] studied how self-efficacy could affect student's engagement in online learning courses held in Virtual Reality Learning Environments (VRLE). The study showed that self-efficacy was a significant predictor of student's engagement. This result was congruent with the finding of Sun and Rueda [37]. Pellas' [29] study also implied that higher levels of self-efficacy facilitate student's engagement with the learning process. In a latter work, the use of a VRLE was also found to increase the perceived self-efficacy of pre-service teachers [27].

This study expected computer self-efficacy to show a similar influence on the student's engagement when using VR. Thus, the resulting hypothesis is:

H2: Self-efficacy will have a significant positive influence on the student's cognitive engagement when interacting with a VR learning environment.

2.4 Cognitive Load and Engagement

According to Paas and van Merriënboer [28, pp. 122], cognitive load is "a multi-dimensional construct that represents the load that performing a particular task imposes on the cognitive system of a particular learner". Sweller's [36] cognitive load theory also sustains that a high mental workload requires the allocation of extra resources for entering information.

Other authors have also studied the implications of physical and perceived measures of cognitive load. A clinical study done by Berka, *et al*. [6] monitored the levels of task engagement and mental workload in vigilance, learning, and memory tasks using an electroencephalogram (EEG). They found a correlation between EEG measures with both subjective and objective performance metrics. They also found that both, task engagement and mental workload EEG-based measures, increased proportionally as the demands of the task increased. Their findings were later confirmed by Makransky, *et al*. [23] who also reported higher EEG measurements of cognitive load as a result of higher levels of immersion achieved by VR environments.

Contemporary studies in the field of VR have found a positive effect of VR experiences on the cognitive load associated with the equivalent task in real life [2, 21].

On the other hand, authors have reported significant increments of cognitive load as a result of the interaction with VR environments. For instance, Schrader and Bastiaens [32] reported an increase in cognitive load as virtual presence increased but, it also reported an increase in students' retention and comprehension.

2.4.1 Multidimensional Approach to Cognitive Load

There are two different approaches to analyzing cognitive load. Although early educational psychology literature recognizes cognitive workload as a multi-dimensional construct [28], its measurements are often done using a global score [15]. Although the NASA-Task Load Index (NASA-TLX) is a construct used by scholars to measure task load, some researchers have used selected dimensions of the index to measure cognitive load [15, 26, 30, 38, 46]. For instance, Gerjets et al. [46] successfully used three dimensions of the NASA-TLX index (Mental demand, effort, and frustration/stress) to measure cognitive load. Their study showed that the groups with the highest learning outcomes reported the lowest cognitive load [45]. The multi-dimensional configuration of the index allows the use of its individual factors in studies involving cognitive load analysis.

Galy, *et al.* [15] showed that it is essential to distinguish the different components of cognitive load included in the NASA-TLX questionnaire. The authors stated that situations involving complex tasks are more likely to need this approach. A few other authors have used this approach previously to study the impact of cognitive load dimensions on the frequency of radiotherapy incidents [26] as well as their impact on human factors affecting flight deck design [38]. In the field of virtual reality, a similar approach was used to analyze the impact of task distribution on cognitive load [30].

In this study, we used the differentiated approach suggested by Gerjets et al. [46] to determine the influence of each dimension of cognitive load on student's engagement when using a VR learning environment. The three dimensions of the NASA-TLX included in this study were defined by Hart [18] as follows:

Mental Demand: The amount of mental and perceptual activity required. How easy or demanding, simple or complex, exacting or forgiving the task was.

Effort: How hard the participant had to work to accomplish the level of performance.

Frustration Level: How insecure or secure, discouraged or gratified, irritated or content, stressed or relaxed, annoyed or complacent the participant felt during the task.

Links of these dimensions of cognitive load with student's cognitive engagement have already been identified by the literature. Some of these dimensions seem especially promising as explained below.

Smiley and Anderson [34] tested factors affecting student's cognitive engagement on assessment tests and found a moderate but significant positive correlation of effort with engagement. They suggested that the effect between cognitive engagement and effort may be bidirectional. To explain that, they asserted that students may invest more effort in those tasks they find more cognitively engaging and, at the same time, an increased engagement in an academic task may increase the value given by the student to it, and it may result in an increased effort.

This study expected effort to show a similar influence on the student's cognitive engagement when using VR. Thus, the resulting hypotheses are:

H3: Effort will have a significant positive influence on the student's cognitive engagement when interacting with a Virtual Reality learning environment.

A handful of authors have also analyzed the role of frustration level (another dimension of cognitive load) on student's engagement. Hansen and Eddy [17] studied the relationship between engagement and frustration in computer science students. They expected to find some inverse correlation between the two of them. However, they couldn't find statistically significant evidence of such correlation. Then, they decided to divide the analysis by type of task. The decision led them to an interesting discovery. For the tasks where the lowest levels of engagement were observed, qualitative data revealed expressions of frustration from the students. On the other hand, in tasks where the highest levels of engagement were reported, students expressed a full understanding of the problems and the way to solve them. As a result, their expressions evidenced no signs of frustration. Similarly, in a qualitative study, Kahu, *et al*. [20] found evidence of the link between frustration and engagement. They highlighted that frustration triggered by poorly designed materials and high cognitive load impacted negatively student engagement to the point of withdrawal from the course. However, they also found that short-term frustration appeared to have little or no impact on student engagement.

This study expected frustration level to show a similar influence on the student's cognitive engagement when interacting with a VR learning environment. Thus, the resulting hypothesis is:

H4: Frustration will have a significant negative influence on the student's engagement when using a Virtual Reality Learning Environment.

2.5 Theoretical implication

Chi and Wylie [10] discussed an existing link between cognitive engagement and cognitive load from the view of their ICAP (Interactive, Constructive, Active, and Passive) theoretical framework. In principle, learning materials producing a higher cognitive load increase the difficulty of the tasks producing less learning. Conversely, the ICAP theory states that increasing modes of engagement that produce more learning require more effort but impose more load on the learner. They expressed that, although the two theories seem to contradict each other in terms of their predictions, sometimes the two theories may predict congruent results. This is because, at times, increased engagement happens together with increased cognitive load. For example, if students elaborate a self-reflection about their work (a display of increased engagement) they are being constructive and, as a result, their learning will increase. But, by reflecting they are also increasing cognitive load.

3 Methodology

In this section, we first describe the virtual reality learning module used for instruction in the online course. Then, we describe the virtual reality learning environment designed to support the instruction. Finally, participants, data collection instruments used, procedure, and data analysis methods applied are presented.

3.1 Virtual Reality Module

We designed the new virtual reality module to introduce students to the creation of basic 3D virtual reality content for the design of learning environments as part of an existing online digital media course. The eight weeks intensive course also teaches graduate and undergraduate online students how to create digital images, audio, and video to use them for online learning. As part of the course requirements, they had to produce a website with a portfolio containing digital media content created in the class.

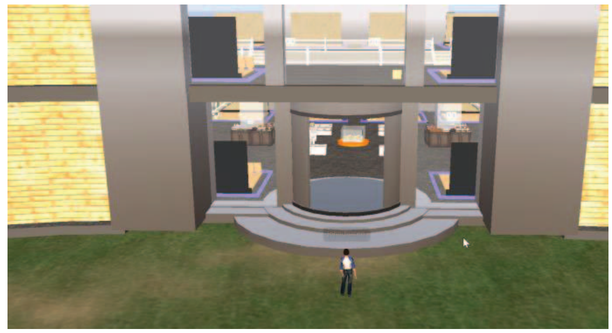

Figure 1: Virtual Gallery.

The software used to host the virtual reality experience is a 3D engine called OpenSimulator [47]. We used Firestorm viewer to navigate the virtual world hosted in OpenSimulator. The instruction about the new module lasted one week but the activities and projects spaned along three weeks of the course. Instructional materials for the new module were added to the existing Digital Media course in Canvas (The University's LMS). The module contains 12 video tutorials explaining how to install the required software, how to connect to and navigate the VR environment, how to personalize their avatar (virtual character), and how to create, edit, and combine prims (3D objects) in the environment. The module also contains activities to encourage students to practice what they have learned and a discussion about potential applications of virtual reality environments for learning.

We built a Virtual Reality Learning Environment as a strategy to integrate the skills acquired during the instruction with the existing modules of the Digital Media course. We instructed students to create and set up virtual media boards in a virtual gallery, a building located in the VR environment (See Figure 1), to showcase their digital media portfolios, visit portfolios created by their peers, and provide feedback to each other about ways to improve their creations. Given the cost of the devices and the different locations of the participants, a desktop-based VR learning environment seemed to be the most appropriate option.

3.2 Virtual Reality Learning Environment (VRLE)

The environment we built for the study resembles a virtual island. The island contains a two-story building called "Virtual Gallery" with furniture and presentation spaces all around it (See Figure 2).

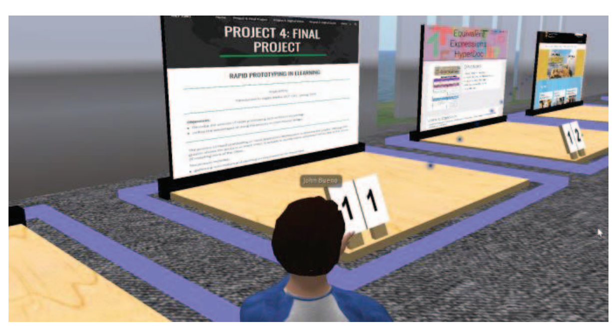

Figure 2: Presentation spaces.

Before interacting with the VR environment, students learned the basics about VR technologies and how they could use them to create interactive learning environments and enhance learning experiences. Then, after receiving their authentication credentials and watching a video tutorial on how to install and setup the viewer, they were required to perform the tasks by themselves. Next, with other video tutorials, they learned how to customize their avatar and navigate the environment. Those were the first activities they were required to perform when they first logged in. In the next step, they learned how to create basic objects, how to move them, rotate them, and scale them up and down. They also learned how to change the texture of objects, how to copy them, how to combine them. They were asked to create a basic room with four walls and a concrete texture. All these activities were performed in a free space outside of the media gallery where they could freely create and edit their objects. After that, they are instructed on how to use the properties of the objects to set up a media board (See Figure 3).

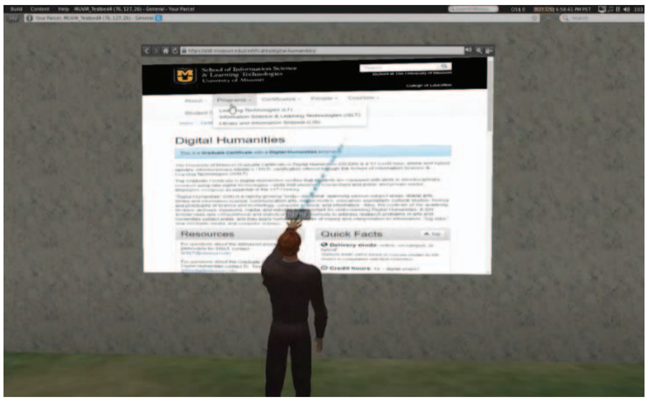

Figure 3: Instructor showing how to create media boards.

A media board allows students to display multimedia content on one of the surfaces of one object. They needed this knowledge to set up their media boards in the gallery to display their websites with their portfolios of digital media. After they learned all the basics about navigation and the creation of 3D objects, they were required to think of a learning scenario that could be designed using the skills they just learned. They posted their ideas in a discussion forum and gave and received feedback from their peers. In the final stage, students were required to create media boards in the gallery to showcase their digital media web portfolios. Spaces in the gallery were numbered and assigned previously to students (See Figure 4). Students did set up their media boards, visited their peer's media boards, and interacted with them to review their peer's creations. They provided feedback about ways to improve their images, audio, and video.

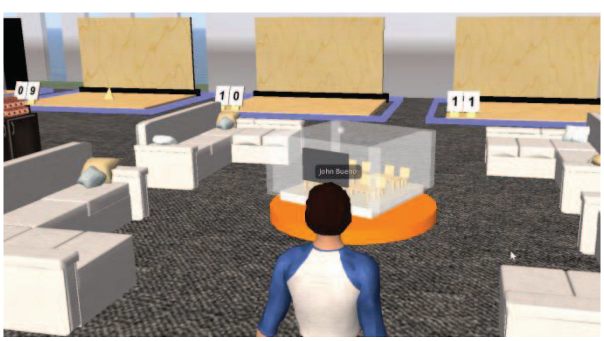

Figure 4: Numbered media boards.

They could interact with their peers by using the chat or by using their microphones and speakers. Thus, the environment was also a meeting place to discuss other educational applications of VR for education.

The whole experience took place during weeks 6, 7, and 8 of the 8-week intensive course. Online students worked at their pace. Less than 10% of the students did not finish the experience.

3.3 Participants

We invited 85 students taking an online module about virtual reality in a land-grant university in the US to voluntarily take part in the intervention. 62 of them completed the online survey after the intervention: 24 males (39%) and 38 females (61%), most of them (84%) in their twenties or thirties. Two of them reported having beginner computer skills, 34 of them (54%) reported having intermediate computer skills, and 26 of them (42%) reported having advanced computer skills. Only two of them reported having high experience with VR environments, 14 (23%) of them reported intermediate experience, and most of them 46 (74%) reported having low or no previous experience with VR.

3.4 Data Collection Instruments

As discussed in section 2.4, we measured cognitive load using three selected dimensions of the NASA-Task Load Index (NASA-TLX), a survey developed by Hart [18] using an approach previously suggested and used by other authors [15, 26, 30, 38, 46]. Dimensions included in this study were mental demand, effort, and frustration level. Self-reported measurements of cognitive load dimensions were done on 1-6 Likert scales.

We also measured engagement and presence using the student engagement survey, an instrument developed by Smith [35]. The survey consists of 15 items. The first 8 items evaluate cognitive engagement and the last 7 items evaluate presence. Answers to items of the survey were also set using a 1-6 Likert scale.

We developed additional questions to measure students' reported self-efficacy when performing tasks in the virtual reality learning environment. The questionnaire has 6 items using a 6 levels Likert scale.

To assess the reliability, we conducted a Cronbach's alpha test. The overall reliability was 0.76 (95% *CI* [0.65, 0.87]), which was acceptable. Specific reliabilities for each factor ranged from 0.70 to 0.79.

3.5 Procedure

A survey was distributed among 85 online students before starting the module on VR in the Digital Media course. Participation in the study was voluntary (IRB approval was sought before the study).

The VR module took one of the 8 weeks of the intensive course but all activities spanned 3 weeks. The first week of the virtual reality module focused on providing instruction about the functioning of the 3D virtual environment. The remaining two weeks included practical activities and a discussion.

Students were first required to install and set up the virtual reality viewer (Firestorm) to connect to the virtual gallery. Then, they had to customize their avatar and learn how to navigate the environment. The next steps were about learning how to create basic 3D objects, setting up a media board with their digital media creations, visiting their peers' portfolios, and providing feedback to them. The last activity was a group discussion that took place synchronously in the environment about other possible applications of VR for learning.

A post-survey was administered after the module ended at the end of the 8-week course. 62 of the participants filled up the survey.

3.6 Data Analysis

We used Pearson's correlation analysis to explain if presence, self-efficacy, and individual dimensions of cognitive load (mental demand, effort, and frustration) could predict student's engagement. Additionally, we used hierarchical regression analysis to see whether adding additional variables significantly improved the model's ability to predict engagement.

These methods were applied to specifically determine the following: (1) What factors influence student's cognitive engagement when learning in a 3D VR learning environment? (2) What subset of these factors explains better the variance of student's cognitive engagement in a 3D VR learning experience?

4 Results

Pearson correlations (Table 1) indicate that presence (r=.57, p<.001), self-efficacy (r=.41, p<.01), performance (r=.59, p<.001), and effort (r=.33, p<.01) were positively related to student's engagement. Frustration (r=-.42, p<.001) was negatively related to student's engagement.

Table 1. Descriptive statistics and correlations

Measurement Variable	1	2	3	4	5	6
1. Engagement	-					
2. Presence	.57***	-				
3. Self-Efficacy	.41**	.27*	-			
4. CL-Mental Dem	.15	.13	-.03	-		
5. CL-Effort	.33**	.14	.09	.48***	-	
6. CL-Frustration	-.42***	-.29*	-.21	.36**	.27	-
Mean	4.76	4.29	4.31	4.48	4.44	3.97
SD	.74	1.19	1.05	.90	.86	1.41
Skewness	-.64	-.45	-.31	-.02	.12	-.22
Kurtosis	.72	-.25	.27	-.24	-.68	-.79

*p<.05; **p<.01; ***p<.001

A simple linear regression model (Table 2) with presence predicting engagement was significant, $F(1,60) = 28.16$, $p < .001$, and represented a large effect (R^2 = .32). A second model incorporating self-efficacy was also significant, $F(2,59) = 18.74$, p<0.001, represented a large effect (R^2 = .39), and accounted for significantly more variance ($\Delta R^2 = 0.07$, $p < .05$) than the model with presence alone. However, a third model incorporating the two dimensions of cognitive load that showed a significant correlation with cognitive engagement - effort and frustration - accounted for significantly more variance ($\Delta R^2 = 0.17$, $p < .001$) than the model with presence and self-efficacy alone. Diagnostics for the model noted no concerns with influential cases, and assumption testing found no concerns with multicollinearity, normality, homoskedasticity, and independence of the error. The more complex model was significant, $F(5, 56) = 17.97$, $p < .001$ and represented a large effect ($R^2_{adj} = 0.56$) as it accounted for 56% of the variance in engagement. Presence significantly predicted engagement while controlling for self-efficacy, effort, and frustration level, $t(56) = 3.61$, $p < .001$. Self-efficacy significantly predicted engagement while controlling for presence, effort, and frustration level, $t(56) = 2.16$, $p < .05$. The results also indicated that effort significantly predicted engagement while controlling for the other variables $t(56) = 3.86$, $p < .001$, and frustration significantly predicted engagement while controlling for the other variables $t(56) = -3.77$, $p < .001$. Effort ($\beta = 0.32$) had the strongest effect on engagement while controlling for the other variables in the model while self-efficacy ($\beta = 0.14$) had the smallest effect on cognitive engagement.

Table 2. Summary of Hierarchical Regression Analysis

Variable	β	t	sr^2	R	R^2	ΔR^2
Step 1				.62	.32	
Presence	.35	5.31***	.07			
Step 2				.59	.39	.07*
Presence	.31	4.63***	.07			
Self-efficacy	.19	2.58*	.07			
Step 3				.51	.56	.17***
Presence	.22	3.61***	.06			
Self-efficacy	.14	2.16*	.07			
CL-Effort	.32	3.86***	.08			
CL-Frustration	-.20	-3.77***	.05			

*p<0.05; **p<0.01; ***p<0.001

Qualitative data supported our findings from the quantitative analysis. Many participants were excited about the VR learning experience and enjoyed "*the freedom to explore and practice in Firestorm*." For many of them, it was their first time taking a course in a VR environment. Someone described the VR environment as "*expands my mental horizon as for ways to learn beyond the traditional pencil paper*." Another one admitted that "*It definitely helps to remove some of the intimidation and mystery around creating and interacting within a VRLE, especially showing that goggles or additional equipment are not necessary.*" As for their engagement, one participant mentioned, "*The actual experience where you are applying these concepts and fully engaged was incredible*." Another participant said, "*I was shocked at how much time I spent playing around with my avatar! Haha. I continued to change its clothes and appearance*." These examples illustrated that the participants were highly engaged in the VR learning environment and satisfied with this extraordinary (for them, at least) learning experience.

5 Discussion

This study addressed the questions: What factors influence student's cognitive engagement when learning in a 3D VR learning environment? What subset of these factors explains better the variance of student's cognitive engagement in a 3D VR learning experience?

Using data collected from online graduate students enrolled in a digital media course, we provided empirical evidence of the influence of presence, self-efficacy, and cognitive load on student's engagement while working in a 3D desktop-based VR learning experience. In this study, we considered three of the six dimensions included in the NASA-TLX index [19] to measure cognitive load in an approach previously suggested and used by other authors [15, 26, 30, 38, 46].

The results of the analysis presented in Table 1 showed that presence significantly predicted student's engagement, thus confirming hypothesis H1 (Presence will have a significant positive influence on the student's cognitive engagement). This finding is consistent with [9] and [13]. Presence is a relevant construct in VR studies since it is a sensation inherent to 3D virtual reality learning environments [12]. This finding encourages the use of VR as instructional technology.

Self-efficacy also showed an important effect as a predictor of student's engagement, thus confirming hypothesis H2 (Self-efficacy will have a significant positive influence on the student's cognitive engagement). This view is supported by existing studies that have shown a similar influence in the context of VR [27, 29] and other contexts [37]. From these results, it can be implied that to engage students, faculty should find ways to encourage self-efficacy in their students rather than merely relying on the presence achieved by individuals using virtual reality. Margolis and Mccabe

[24] suggested strategies for strengthening students' self-efficacy. Some of them could be applied to instruction using VR learning environments. One of the strategies may be using difficult tasks moderately. VR can be intimidating and difficult for students with no prior experience. So, tasks should be planned carefully and scaffolded appropriately so they are not too difficult. Another strategy is to capitalize on students' interests. Since some of them are not into gaming they tend to believe that VR is for gamers and have a low expectation about VR learning environments. But, we observed that when they work on projects of their interest they seem to forget they are not gamers and get involved. Also, prompt feedback is indicated as an effective strategy to encourage self-efficacy.

One of the highlights of this study is the contribution of two of the three dimensions of cognitive load (effort and frustration level) to explain the variance of cognitive engagement. The significant correlation between effort (one dimension of cognitive load) and engagement confirmed H3 (Effort will have a significant positive influence on the student's cognitive engagement). This result may imply that students were not only "willing to invest the necessary effort" [14, pp. 60] on the learning tasks, but they reported a correlated level of perceived effort invested in their interaction with the learning tasks performed in the virtual environment. This seems to confirm that true levels of engagement may drive effective efforts in the learning tasks in virtual environments. And, it may also demonstrate the link between cognitive engagement and cognitive load (at least with some of the dimensions of it) discussed by Chi and Wylie [10] from the lenses of the ICAP theoretical framework.

Finally, frustration level (another dimension of cognitive load) was also identified as a significant predictor of student's engagement, thus confirming hypothesis H4 (Frustration will have a significant negative influence on the student's engagement). Although in a smaller magnitude, this means that students experiencing stress associated with their interactions with the VR technology may display a reduced engagement with the learning activities. This is in harmony with the findings of previous studies [20, 17]. This study is probably one of the first quantitative studies in VR demonstrating the influence of frustration as a dimension of cognitive load on student's engagement in VR environments. It implies that strategies designed to reduce student frustration levels when using virtual reality learning environments should be considered to enhance engagement. Students who are regular gamers are more familiar with navigating and performing basic operations in this type of technology. Those with experience in other virtual worlds would find VR environments created in OpenSimulator very familiar to what there are used to. However, most of our participants reported little or no experience with the VR environment. We observed that first-timers usually struggle to navigate the environment and to accomplish the tasks given. This might be a source of frustration and, as the results of this study showed, it might affect their engagement. Scaffolding strategies aimed to reduce the frustration of first-timers may be required too. In this experiment, we provided students with video tutorials about every step of the process. Finding the proper version for their system, installing and setting up the viewer, and learning how to navigate the environment were demonstrated. Still, based on their questions posted on the discussion board, we noticed that not all of them watched all the video tutorials and some of them experienced problems when performing basic operations explained in the tutorials. Prompt technical support and online facilitation are also important strategies to reduce frustration.

5.1 Limitations

Limitations of this study include a relatively small sample size and a homogeneous study population, predominantly young individuals with intermediate to high computer skills. In addition, most students were new to this type of technology which could have influenced their self-reported engagement levels due to the innovation factor. Also, being online students, all participants used their own hardware, platform, and internet connection. Differences in computational power, internet speed, and connection reliability could have influenced their overall experience and may have introduced a confounding factor. An additional limitation was related to pre-training exposure. All students were provided with training materials previously to experiencing the activities in the VR environment. However, differences in the time spend in pre-training activities might have influenced the effort required, the perception about their performance, and the frustration level experienced.

Another important aspect to be improved in future iterations is the use of widely accepted instruments to measure engagement and presence. Since Smith [39] does not include information about the validity and reliability of the instrument we discourage its use. Thus, we recommend the use of standardized questionnaires to measure engagement [39, 40] and presence [42, 43, 44].

All these aspects open possibilities for future studies.

6 Conclusion

A proper understanding of the factors affecting student's cognitive engagement in Virtual Reality Learning Environments can lead to designing more effective learning experiences. Some of them, like presence, are inherent to this type of technology where higher levels of immersion are achieved. However, others, like self-efficacy, may be fostered by the way learning tasks are designed in the environment and by the strategies implemented by teachers. Understanding the influence of individual dimensions of cognitive load on student's cognitive engagement proved also relevant. Finding strategies to reduce student's frustration and increase their effort levels are likely to impact their levels of engagement and, therefore, their learning outcomes.

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