Virtual Reality Computer Learning

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1 INTRODUCTION

Introduction of technology has always changed education. Blackboards, whiteboards, overhead projectors, PowerPoint, and countless other advancements in educational tools have paved the road to the learning structures we use today. The incorporation of technology in education has been a continuously evolving process over many centuries, with innovations transforming the way education is both delivered and received[1]. Computer science has, and will, continue to harness the forefront of technology to provide the best and most efficient teaching methods possible. One of these emerging techniques uses gamification of learning. Gamification in education has shown to improve the engagement and motivation of students, enhancing learning outcomes[2]. As opposed to using a to-do list of tasks to be completed in order to satisfy a curriculum, studies have been conducted harnessing virtual reality environments. By creating fun, engaging material in virtual reality, the complexity of learning is reduced, interest and motivation are increased, and graduation rates in courses are boosted[3]. The use of more innovative technologies in learning, such as virtual reality, have recently been shown to produce noticeable improvements in performance[4][5]. This project seeks to compare the benefits of virtual reality learning to that of a more traditional learning environment relating specifically to the computer science field. Measuring any potential benefits and finding ways to apply them to teaching specifically at the collegiate level in relation to computer science could lead to future improvements in technology and result in more enthusiastic, proficient computer scientists entering the field. As technology evolves given its continuously advancing nature, it is important to explore the potential benefits of innovative educational tools such as virtual reality. We are pursuing this in our study because of the importance of fostering the growth and acceptance of technology that can positively impact the lives of many students and teachers alike[6].

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2 RELATED WORK

Research has already shown the potential for virtual reality training to help students learn faster, make more accurate decisions, and remember concepts longer [7]. This has been demonstrated in many scientific fields including engineering [8], medicine [9], biology [10], and computer science. The interactive nature of virtual reality promotes understanding and stimulates users while encouraging exploration and growth [11]. There are several motivations for utilizing virtual reality in education, including its ability to create immersive, engaging learning experiences, its capacity to support hands-on learning and simulations, and its potential to provide access to remote or otherwise difficult-to-reach learning environments [12].

Education occurring within a virtual environment has yet to be widely integrated into educational practices. Because it's use is relatively uncommon it is often a unique experience for students. This novelty in addition to the endless possible applications of virtual environments activates a state of generative learning for students. Generative learning is a theory that involves the active integration of new ideas and experiences with the learner's existing schema [13]. The core concept of generative learning is that, in order to learn with understanding, a learner has to construct meaning actively [14]. This technique hinges on implicit cognitive participation. Deriving significance by generating relationships and associations between active stimuli and existing knowledge and experiences promotes motivation, retention, engagement, understanding, and utilization [15] [16] [17]. Virtual reality and it's related counter parts, augmented reality and mixed reality, engage in generative learning through the induction of embodied interaction. Embodied interaction describes "the interplay between the brain and the body and its influence on the sharing, creation and manipulation of meaningful interactions with technology" [18]. Embodied interaction develops and enhances the engagement of spatial skills therefore enriching the acquisition, organization, utilization and revision of knowledge gained from educational interactions within spatial environments. Spatial skills, when used in a virtual environment to physically manipulate and interact with a simulation enable an immersive and engaging method of interfacing with learning material and exercises to provide unique learning opportunities that are not possible with other types of traditional instruction. The embodied interaction observed within virtual simulations activates generative learning which is proven to help students develop deeper understanding and retention of complex concepts [19].

Research has also demonstrated the benefit of using virtual reality to teach beginning programming concepts to both children and adults [20]. Many iterations of this research target their goals toward younger children in classrooms [21]. Being generally more adaptable and enthusiastically geared toward learning they have shown to be great subjects for these experiments [22], but advancements in learning should be applicable to a range of individuals or conclusions at least tested on different groups for comparison. The research has been persuasive, but while some have tried [23] few works pertain exclusively to teaching programming or attempt to teach the complex algorithms present in computer science. Furthermore, other experiments delve into complete gamification. Instead, we aim to investigate these systems' potential at their core by breaking down the most basic differences between the virtual and conventional education. Our Virtual Reality experiment is distinct from previous work conducted in the field because of it is evaluating purely based on experience and not delving into deeper more interactive or potentially confounding elements [24].

3 METHODOLOGY

This experiment was designed to compare students ability to learn from traditional teaching techniques to that of virtual reality teaching. We have developed a virtual reality based learning tool using Unreal Engine that was administered via a virtual reality headset. This prototype tool provided participants with a virtual environment walking them through the learning material and helping them understand and learn the basics of utilizing binary search trees. The students were taught the algorithm necessary for sorting elements into a binary search tree data structure. Our intention was that once these concepts were demonstrated to the student in virtual reality they would then be able to recognize and replicate the process. The application demonstrates a 3-Dimensional diagram displayed in front of the participant which proceeds through the steps of sorting a binary search tree. Spherical nodes representing number values move dynamically during this live demonstration. A voice over accompanied this display to explain details of the demonstration.

3.1 Participants

A total of 20 participants were selected to partake in this study; 10 completed the experiment with the virtual reality learning method and the other 10 learned via a conventional video. The demographic of participants consisted of those mostly within the 19-25 age range with only a few exceeding this range. A good balance of gender was achieved with 9 female participants and 11 male participants. Many subjects were selected from the population of students studying at Colorado State University. Researchers attempted to find individuals who didn't have prior experience with binary search trees and its sorting algorithm since our study aimed to measure the learning of this concept. However, a potential issue due to the accessible population pool was that many available participants were connected in some way to the field of computer science. Several subjects were either enrolled in computer science classes currently or in the past, with some majoring in the field. This introduces a confounding condition in which certain participants may have prior knowledge of the aforementioned algorithm and data structure. Researchers were aware of the potential inconsistencies that could result from these outliers and therefore measures were taken to account for this factor. Subjects' prior knowledge of binary search trees and their level of confidence performing a sorting operation was measured before the learning method was applied. Precisely the same assessment was used before learning as after so that the exact difference achieved from the learning method could be calculated. Therefore the bias of a subjects previous experience was eliminated. Another important note was that a few participants who learned via the virtual reality method required eyeglasses. The logistics of a virtual reality headset presents possible difficulties for these individuals, such as difficulty wearing the headset or motion sickness. Ishii et al. (2001), suggests that the physical distance between eyeglasses and the lenses of the headset can cause issues with visual accommodation, leading to an increased risk of motion sickness [25]. Researches minimized these issues as much as possible by providing a glasses spacer to improve comfort. However this matter must be mentioned since it may potentially influence the degree of learning or enjoyment of learning within the virtual reality learning group. Since our experiment was run on a limited population of university students in their early-mid twenties the results should be interpreted with this in mind, limited to that demographic and not necessarily applied to other groups such as school children, elderly adults, and people with a lower than university level of education.

3.2 Apparatus

The experiment was run through Unreal Engine 5, and Oculus Quest 2 headset

on an Alienware desktop computer. The following packages are required:

-JDK 1.8.0.77 (jdk-8u77-windows-x64.exe)

-SDK 23.0.3//25.0.3//29.0.2//30.0.3//31.0.0//32.0.0

-NDK 21.3.6528147.

The experiment also requires an area where the user can be seated, or room to stand, for the duration of the experiment.

3.3 Procedure

All participants were volunteers and in order to participate, subjects where required to a sign a consent form ensuring confidentiality and indicating expectations, requirements, and any potential risks. After agreeing to participate the subjects where briefed before the experiment by a researcher who fully explained the purpose of the experiment and gave a short description of each step. Subjects were then asked to fill out a google form to record their demographic information. Next each participant was given a questionnaire to measure their previous knowledge about binary search trees. This evaluation included two tasks requiring subjects to sort numbers from a provided queue into a binary search tree data structure. The template of the tree data structure was provided and the subjects only needed to fill in the blanks with the values from the queue. These two questions were designed to reflect those that would appear on a university exam covering binary search trees. After completing these two tasks, the questionnaire asked participants to rank their understanding of how to build a binary search tree from 1 to 10, 1 indicating no understanding and 10 meaning they fully understood. Once the subject completed the pre-learning questionnaire they proceeded to the learning portion of the experiment which used a between-subjects design. Students were split evenly into two equally sized groups at random; one group learned using the virtual reality prototype application, and the other learned using a video based upon those commonly given to students in university courses. Both methods were controlled heavily to ensure that the same information was presented for the same duration. Participants were only allowed to receive the learning instruction once. After the learning period both groups were asked to answer the exact same questionnaire as before to measure their comprehension after learning from their respective method. This enabled a subjects performance before and after learning and the degree of improvement to be measured explicitly. The sorting tasks did not change so that the difficulty of the questions was not a factor in the subjects performance. By asking the participant their own perceived level of understanding both before and after learning, their change in confidence around the subject was also measured. The post-learning questionnaire also included an additional question asking subjects to rank how much they enjoyed the process of learning about binary search trees. Participants were not given a time limit for either questionnaire which resulted in some variation on the length of the experiment. Once the last participants completed the post-learning questionnaire they were debriefed appropriately, thanked for participating and any remaining questions they had were answered which concluded the experiment. Results were graded by the researchers according to an answer key. Improvement of performance and perceived comprehension after learning was calculated, statistically analyzed, and compared between groups to asses the effectiveness of each learning method.

3.4 Experiment Design

The experiment was a between-subjects design with one independent variable, the learning method. Subjects where divided into two groups. One group for each of the two conditions of the learning method, either the virtual reality prototype or the conventional video instruction. Three dependent variables were measured, test performance improvement, perceived comprehension improvement, and learning enjoyment. Test performance improvement was calculated as a score indicating the difference in how many incorrect answers a participant gave before versus after the learning period which used a ratio scale of measurement. Perceived comprehension improvement was determined as the difference in rating before versus after the learning period which used the interval scale of measurement. Learning enjoyment was measured based on the ranking given by the participant after the learning period which uses the interval scale of measurement. A control condition of this study was the baseline control measured by the participants answers on the pre-learning questionnaire which establishes a baseline for participants skill and confidence before learning and also provides the comparison necessary for the dependant variables. Other control conditions of this experiment were standardized protocol which includes factors such as participants not receiving special treatment or intervention ensured by instruction scripts followed by researchers refusal to answer questions about concepts on the test during the trials. The significance of this control is supported by Tse et al. (2010) who concluded that standardizing testing procedures and instructions is important for accurately assessing the effects of learning from tests [26], and Gog et al. (2012) extends this to computer-based learning environments as well [27]. This design establishes the validity and reliability of the results since confounding variables are controlled for and factor into the analysis of the results. Additional confounding variables that remain uncontrolled were participants stress level, amount of sleep, academic level, previous computer science history and previous experience in virtual reality. These factors could possibly influence the results but were not the focus of this study.

4 RESULTS

Overall Learning Improvement

Data Summary				
Groups	N	Mean	Std. Dev.	Std. Error
VR	10	13.7	9.6154	3.0407
Video	10	14.1	8.3858	2.6518

Fig. 1. Overall learning improvement Data Summary.

Anova Summary					
Source	Degrees of Freedom DF	Sum of Squares SS	Mean Square MS	F-Stat	P-Value
Between Groups	1	0.8	0.8	0.0098	0.9221
Within Groups	18	171.7001	9.5389		
Total	19	1465.798			

Fig. 2. Learning Improvement Anova Summary.

Change in Confidence

Data Summary				
Groups	N	Mean	Std. Dev.	Std. Error
VR	10	4.8	3.1198	0.9866
Video	10	4.3	3.0569	0.9667

Fig. 3. Change in confidence Data Summary.

Anova Summary					
Source	Degrees of Freedom DF	Sum of Squares SS	Mean Square MS	F-Stat	P-Value
Between Groups	1	1.25	1.25	0.131	0.7126
Within Groups	18	171.7001	9.5389		
Total	19	172.9501			

Fig. 4. Change in confidence Data Summary.

The execution of the experiment was seamless and conducted over a several day period. The researchers graded the questionnaires and encoded the data into respective measurement scales. The scores of both questions on the questionnaire which test ability to build a binary search tree were combined into one measurement for pre and post-learning. An improvement metric was calculated based on the difference in this score from the pre to post-learning. There are several observations about the collected data that are important to note. Only two participants, one from each group, received a perfect score on the pre-learning test questions. Both of these subjects reported a 10 out of 10 on their confidence for building binary search trees which indicates they were already familiar with the concept and sorting algorithm beforehand. These subjects were not intentionally placed in separate groups due to any counter

Enjoyment

Data Summary				
Groups	N	Mean	Std. Dev.	Std. Error
VR	10	7.7	2.7508	0.8699
Video	10	8.6	4.1419	1.3098

Fig. 5. Enjoyment Data Summary.

Anova Summary					
Source	Degrees of Freedom DF	Sum of Squares SS	Mean Square MS	F-Stat	P-Value
Between Groups	1	4.05	4.05	0.3276	0.5741
Within Groups	18	222.5001	12.3611		
Total	19	226.5501			

Fig. 6. Enjoyment Anova Summary.

Initial Skill

Data Summary				
Groups	N	Mean	Std. Dev.	Std. Error
VR	10	18.9	8.0753	2.5536
Video	10	18.1	6.6072	2.0894

Fig. 7. Initial skill Data Summary.

Anova Summary					
Source	Degrees of Freedom DF	Sum of Squares SS	Mean Square MS	F-Stat	P-Value
Between Groups	1	3.2	3.2	0.0588	0.8112
Within Groups	18	979.7901	54.4328		
Total	19	982.9901			

Fig. 8. Initial skill Anova Summary.

balancing effort and were sorted separately due to pure happenstance. Both of these subjects scored the same on the post-learning test as well which indicates that there was no decrease in knowledge or confidence after learning. These two subjects were the only participants to rate there confidence a 10 out of 10 on the pre-learning questionnaire while almost all other subjects ranked their confidence low, between 1-3, and scored the maximum or close to the maximum possible incorrect answers which would imply all other participants were unfamiliar with binary search trees. 5 out of 10 participants from both groups received a perfect score on the post-learning test but not the pre-learning test indicating they had fully learned the principle of binary search trees and how to sort them. 4 subjects in the virtual reality learning group marked their confidence a 10 out of 10 after learning but before learning scored their confidence low, between 1-3. This shows that they felt fully capable of building a binary search tree. However, only a single participant in the conventional video instruction learning group falls into that description and that number remains the same even if you include subjects who marked their confidence a 9. An incident worth mentioning pertains to a participant in the virtual reality learning group who wore their prescription eyeglasses under the headset during the

Initial Confidence

Data Summary				
Groups	N	Mean	Std. Dev.	Std. Error
VR	10	2.8	2.7406	0.8667
Video	10	2.5	3.2404	1.0247

Fig. 9. Initial confidence Data Summary.

Anova Summary					
Source	Degrees of Freedom DF	Sum of Squares SS	Mean Square MS	F-Stat	P-Value
Between Groups	1	0.45	0.45	0.05	0.8256
Within Groups	18	162.0997	9.0055		
Total	19	162.5497			

Fig. 10. Initial confidence Anova Summary.

learning phase. This participant reported motion sickness and even though they decided to complete the learning phase they reported feeling nauseous and faint after the learning method was completed. This participant scored a 1 out of 10 on the enjoyment of learning question. This is a valuable observation because it provides tangible evidence of motion sickness while using virtual reality headset which is clearly a flaw and a potential downfall of virtual reality in general for certain individuals. This score might be considered an outlier since it pertains to physical symptoms caused by virtual reality and not necessarily the actual enjoyment of the learning method.

Some descriptive statistics of importance are as follows; for the questionnaire section which measures the ability of participants to build a binary search tree, the maximum possible score was 24. Initial skill in this study is being measured by the number of incorrect answers given on this section, meaning that a larger number, with a maximum of 24, indicates less skill and a lower number indicates more experience with the concept of binary search trees. The mean initial skill of the virtual reality group was 18.9 and the mean of the video group was 18.1 (fig. 7). Confidence building binary search trees was measured from 1-10, 10 being most confident. The mean initial confidence of the virtual reality group was 2.8 and the mean of the video group was 2.5 (fig. 9). Learning improvement was measured as the difference between the initial skill score and the post-learning skill score. An improvement score of 24 means that a participant got 24 more answers correct on the post-learning skill questions than the initial skill questions. The mean improvement score of the virtual reality group was 13.7 and the mean of the video group was 14.1 (fig. 1). Change in confidence was measured as the difference in the post-learning confidence score from initial confidence score. The mean change in confidence score of the virtual reality group was 4.8 and the mean of the video group was 4.3 (fig. 3). Learning enjoyment was measured as a score from 1-10, 10 indicating the participant got maximum enjoyment from the learning process. The mean learning enjoyment score of the virtual reality group was 7.7 and the mean of the video group was 8.6 (fig. 5).

4.1 Data Analysis

In this experiment parametric data was collected from a between groups study using ratio and interval scales of measurement. The one-way Analysis of Variance (ANOVA) statistical formula was chosen as the appropriate analysis strategy to compare the data across the two groups. A significance level of $p < .05$ was used to determine the statistical significance for the data collected on both groups. An ANOVA was run to determine if there was a statistically significant difference between the initial skill of the virtual reality learning group and the conventional video learning group. With a p-value of .8112, it appears that there was no significant difference of initial skill building binary search trees between both groups (fig. 8). Another ANOVA was conducted to investigate a significant difference in the initial confidence between both groups resulting in a p-value of .8256 indicating no significant difference (fig. 10). When an ANOVA was run to ascertain the significance of the learning improvement data, the results show no significant difference in overall learning between groups with a p-value of .9221 (fig. 2). Another ANOVA was conducted to determine if the change in participants confidence building binary search trees from before and after learning was significantly different between groups and a p-value of .7216 establishes that the difference is not significant (fig. 4). The final ANOVA run resolves whether or not the difference in learning enjoyment was statistically different between groups. However, with a p-value of .8699, there was no statistical difference (fig. 6). In summary, examining all ANOVAs indicates that there was no statistically significant difference in the data collected from the virtual reality group and the conventional video learning group in any of the metrics (initial skill building binary search trees, initial confidence building binary search trees, post-learning improvement building binary search trees, post-learning change in confidence building binary search trees, and enjoyment of the learning method).

5 DISCUSSION

The ANOVA analysis of our data concludes that the virtual reality learning prototype is not significantly better or worse at teaching students the principles of binary search trees than the conventional video method based on the metrics that we studied. This outcome is valuable because it determines that within the measures of this study, virtual reality is as effective of a teaching method as the widely used conventional video approach which may extend to other traditional methods. Video learning has become extremely integrated in the modern learning environment as was concluded by Guo et al. who found that video lectures are widely used in Massive Open Online Courses and that videos can increase student engagement and satisfaction [28]. Hegarty et al. furthers the impact of video based learning, showing that video animations were more effective for learning complex scientific concepts compared to static diagrams or narrated slide shows [29]. It is undeniable that video learning has become a dominate form of education. The implications of that in the context of this study are crucial. We found that virtual reality learning comprehension and enjoyment is comparable to that of video learning which is already largely adopted and highly effective. This shows great promise for the future of virtual reality learning. Interest around virtual reality continues to grow especially among university students. Huang et al. shows that college students had positive attitudes towards virtual reality as a learning tool, with many indicating that it was more engaging and enjoyable than traditional classroom instruction [30]. With increasing demand, more organizations are beginning to explore virtual reality as a learning option. When Romero-Hall et al. investigated the scope of virtual reality usage in 2020 they found universities are indeed using virtual reality for learning across a range of disciplines and found that it is being used for a variety of purposes, such as simulation-based learning, language learning, and anatomy instruction. [31]. If the adoption of video learning is any indication of the possible widespread integration virtual reality learning might see, the future of virtual reality in education is exceedingly bright.

Technology integration is a significant consideration to the success of new education technologies. Bauer et al. studied the factors hindering video and multimedia technology integration in schools. Overall, the study suggested that successful technology integration requires more than just the provision of hardware and software. It also requires adequate training, planning, leadership, and support to ensure that teachers have the knowledge, skills, and resources to effectively use technology in their teaching [32]. This degree of integration is daunting and resource intensive but when executed properly Bauer found that teachers who were trained in technology integration were more likely to use video and multimedia in the classroom and reported higher levels of student engagement and learning [32]. These findings likely extend to the integration of virtual reality infrastructure and highlight a barrier to the integration of virtual reality into education. However, if the widespread use and success of video learning is any indication of the future of virtual reality learning, then if is only a matter of time before we see meaningful integration.

Some research does indicate potential downfalls of virtual reality learning. A study conducted by LaValle et al. in 2018 discusses how some interfaces used in virtual, augmented, and mixed reality can be distracting, which can negatively impact learning and performance [33]. In a 2020 study, Saredakis et al. elaborates on this research showing that factors such as the quality of the virtual reality technology, the type of instruction provided, and the level of interactivity all influence the effectiveness of virtual reality based instruction [34]. These are essential factors to consider during the integration process since they may determine the success of virtual reality educational practices and public opinion about virtual reality in the context of learning or in general. Our study does not support that virtual reality instruction hinders learning in anyway that video learning does not. In other contexts many design and implementation factors may be extremely important in determining the successful integration of virtual reality learning into educational environments.

There are some considerations of note about our particular study. There was an outlier in the enjoyment of learning data for the virtual reality learning group. As previously mentioned a participant became motion sick during and after the virtual reality instruction period rated their enjoyment of the learning method a 1 out of 10. Ragan et al. studied negative outcomes from symptoms reported from virtual reality such as disorientation and cybersickness, which can negatively impact learning [35]. The participants low rating was attributed to this motion sickness and while this is a downfall of virtual reality it does not necessarily reflect a dissatisfaction of the virtual reality learning process. Therefore it should be noted that the enjoyment data and analysis was influenced by this outlier and the enjoyment of the virtual reality learning method might have been skewed more negatively because of this. Another consideration addresses subjects who had no incoming knowledge of binary search trees. The amount of answers these participants got wrong on the pre-learning test is somewhat random within a certain margin since they had no process to inform their answers. Therefore the overall improvement metric is influenced by that randomness. However this randomness should be assumed to be equal for both groups and therefore this effect would be balance and would not influence the resulting analysis. A valuable statistic to examine which complements the improvement metric is participants who received a perfect score on the post-learning test but not the pre-learning test indicating they fully understand the concept after the respective learning phase. Exactly half of each participants in both groups fall into this category which further supports the conclusions drawn from the statistical analysis run on the data indicating that both learning methods were equally successful at teaching subjects to build binary search trees. Another consideration is the method we used to assessed learning. Our study used a test based assessment of learning but there are other types of learning that can be measured: retention, practical application, spoken examination, etc, and there are many ways to implement these tests. Pellegrino et al. discusses a range of methods for assessing learning outcomes, including traditional tests and exams, authentic assessments (such as essays or projects), self-assessment, peer assessment, and programmatic assessment. Pellegrino et al. emphasizes the importance of aligning assessments with learning objectives to ensuring that assessments accurately reflect the knowledge and skills of students [36]. We could have designed our study around a different assessment method however we determined that for our research the test assessment we designed best reflected the university examinations that are common in higher level education courses. Another assessment factor to note is that there are other options to interpret learning from the test answers such as a pass/fail grade or a percentage of correct answers. These options are different but not necessarily better then the scoring method be used in our research which is adequate in determining level of comprehension.

Strengths of this study are that it was run on mostly students which would be the target demographic for a virtual reality learning product and thus the results are highly applicable. This demographic would be highly skilled in video learning and very familiar with it which gives further validity to our conclusion comparing video to virtual reality learning. Our investigation is highly specific to learning the principles of binary search trees from virtual reality vs video instruction and the precision of this controlled scope gives great validity to our data and analysis. Researchers designed this study to be highly controlled and the learning content closely standardized. Our research contains a verbose and repeatable procedure so that the results can be reproducible. Limitations of this experiment are that a small sample size of 20 participants was used. Dallacker et al. suggests that larger participant samples can increase statistical power, reduce the risk of errors, and produce more representative results [37]. Because we used a specific demographic, the findings of our study can only be generalized to this demographic. A significant limitation of our study was that our virtual reality prototype did not utilize any dynamic interaction or gamification. Virtual reality interaction is proven to be an important design factor contributing to learning as found in a study by Kizilcec et al. in 2018 [38]. Dynamic interaction contributes significantly to embodied interaction which as mentioned previously can have a significant impact on engagement and acquisition of knowledge from educational interactions [18] [19]. However, this leaves the opportunity for additional research on this prototype around adding interaction to virtual reality learning which can be compared to the results from this study.

6 CONCLUSION

In summation, our study implies that virtual learning is equally viable to conventional video learning. Virtual reality also appeared to be as enjoyable as video learning for the participants. Participants also felt equally confident in their newfound knowledge whether they learned via virtual reality or video. As video learning is an older and more conventional way of learning, we can assume that our results point to the idea that virtual reality is as good as conventional methods when it comes to teaching. More specifically, both teaching methods were useful in conveying computer science concepts. However, virtual reality as a learning method would likely be improved with elements such as gamification and integration with other established educational frameworks such as google documents and Canvas. As a new learning method, virtual reality needs to be further integrated with heavily studied learning strategies and theories. virtual reality learning is in it's infancy; the full implications of virtual reality as a learning application is exciting but not yet clear.

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