Teaching Data Structures in Virtual Reality

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ACM Reference Format:
Claire Cortesy, Yanye Luther, Seth Rogers, and James Yost. 2018. Teaching Data Structures in Virtual Reality. *J. ACM* 37, 4, Article 111 (August 2018), 11 pages. https://doi.org/XXXXXXX.XXXXXXX

1 INTRODUCTION

Learning is the most important facet of life when it comes to personal development. This makes teaching even more crucial. The most difficult part of teaching is demonstrating complex concepts in simple ways that incorporate a variety of learning styles. Karen Burke et al. proved that a variety of learning styles boosts student's performance of tests regardless of the topic [9]. While this sounds like an easy problem to solve, trouble arises when the complexity of the topic starts to increase. The topics that are the most important are "both difficult to learn and resistant to correction when misunderstood, [these] are just the kind that are increasingly pertinent in our complex and changing world" [24].The more complex the concept the harder it is to simplify and demonstrate, especially visually. However, virtual reality is starting to change that.

The use cases for virtual reality have dramatically increased over the last few years. The total AR and VR users in the US went from roughly 60 million in 2017 to approximately 180 million in 2023. A 3x increase in 6 years [16]. Every sector is at least curious on how they can implement this relatively new technology into their workflow. One sector where virtual reality has gained a lot of traction has been the educational sphere. New teaching methods are always being tried and tested and one new way to approach teaching has been through virtual and augmented reality.

Many institutions have already done experiments using this new technology in exciting and creative ways. From testing to see if virtual reality teaching methods were more engaging for children with autism [26] to using augmented reality to teach Flemingâs rule in electromagnetism [27].

The field of computer science could benefit greatly from incorporating virtual reality teaching methods. This is because computer science concepts are very abstract and rather hard to convey to visual and kinesthetic learners. While studies have already emerged for visually and kinesthetically other concepts [2], [5], currently the only interactive ways to teach computer science concepts are drawings and just playing around with the code.

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Manuscript submitted to ACM

Our aim to try and teach two data structures, Trie and Red-Black Trees, using virtual reality and then compare it to traditional learning methods. We believe that being able to interact with the tree in real time will make learning the data structures much easier for participants and will ultimately lead to better test performance than strictly learning through conventional means.

2 RELATED WORKS

Existing literature shows the emergence of new teaching methods and frameworks that stray away from traditional whiteboards and hard copy textbooks. Cooper et al. [7] shows the importance of visualizations and animations in introductory programming courses using their proposed 3-D interactive animation tool, Alice. While these visualizations and interactive activities have been effective, tools that allow for interactive custom content such as zyBooks [14] allow for a more tailored learning experience for students. Gordon et al. [14] discusses the transformation from static hard copy textbooks to customizable online textbooks in university computer science and engineering courses.

Augmented and virtual reality have been utilized as a teaching method to further push the boundaries of visual and interactive learning. Research involving the use of virtual reality in conjunction with education have been going on for the last thirty years. Initial research grossly underestimated the timescale it would take for VR to migrate into classrooms as seen through Helsel's 1992 claim that, "...the majority of widespread end-user will not be available...maybe as long as five years from now" [15]. While it has taken longer for VR to be rolled out into education, this wait has allowed for further research on the benefits of VR learning to be published. B. Marks open VR lab found that 71% of the engineering students students said the VR teaching enhanced their learning [21]. While Fengxia Li found 85% of participates found it easier to understand topics in VR [18].

However, B. A. Clegg finds that VR only increased perception of learning, not actually learning [6]. In this experiment they used VR as a way to show a video as a medium of explanation for a task. This is a passive approach to learning. This perception of learning stems from an increased motivation to learn [4]; it is unclear if this increased motivation would last after the newness of the virtual learning environment wears off. There are also ethical concerns that VR and AR when interacting with learners who don't fit the coded conceptual model will be left behind without the safety net of direct human influence on education [28]. It is worth noting that VR has already been found to be a useful tool when working with humans who have learning disabilities, a group that currently struggles in traditional learning environments. The greatest benefit came from providing well-controlled sensory stimuli tailored to the needs of users [8].

The research of using virtual reality for education involve two main groups: adult vocational training and university education [11]. In 2014 nearly 22% on published papers were related to medical uses and 66% of papers related to computer science [11]. AR and VR are currently being utilized to teach data structures [19]. Narman et al. [23] used an AR based application to teach ArrayLists, Stacks, and LinkedLists where students would passively watch the data structure manipulation in real time, this is similar to B. A. Clegg's method; however, this not the best way to use VR or AR in learning. Mahmoud et al. [20] claims one of the main benefits with an immersive VR learning environment is the engagement it allows. When immersed in an interactive application explicit guidance accompanied by practice is more effective when learning new content. Agrahari and Chimalakonda [3] demonstrated this by providing instructions to users along each step to avoid misinterpreting the learning experience in their augmented reality application teaching Abstract Syntax Trees. Neha Tuli, found that students test scores rose between 3-3.6 points when they used the interactive technology. Proper immersive and interactive VR/AR teaching can lead to an increase in students scores [27].

3 METHODOLOGY

3.1 Experiment Design

A total of twenty students were taught two different types of data structures, Red-Black trees, and Tries. Both are tree structures, and are similar in their comprehension level [12, 13]. The students were participants from the CS165 Data Structures and CS220 Discrete Structures courses at Colorado State University. This level was chosen as the participants should have enough background knowledge of coding and basic data structures such that they could understand Red-Black trees and Trie. The data structures being taught as part of this experiment are not taught in either of the courses. Participants willingly signed up to be part of the experiment via a website. Consent was collected along with basic demographic information, including: contact info, major, age, ethnicity, years of computer science experience, GPA range, and if they have had experience with the data structures before. Participates were offered extra credit in their courses for participating in this experiment.

20 participants were assigned to one of two experiment groups utilizing a within-subjects design. A total of ten participants were in each group. Each participant from a group traded off if they did control or VR medium first in order to counterbalance any potential learning effect.

Participants took an initial pre-learning quiz on the data structure to get a baseline of what they know. From here they started their learning of the data structure in their respective medium. Each participant was capped at fifteen minutes for learning, in VR or in control; however, they were not required to spend the full fifteen minutes learning. After completing the learning activity, participants took a post-learning quiz about what they have learned. They then went immediately into learning the next data structure in the opposite medium, repeating the process.

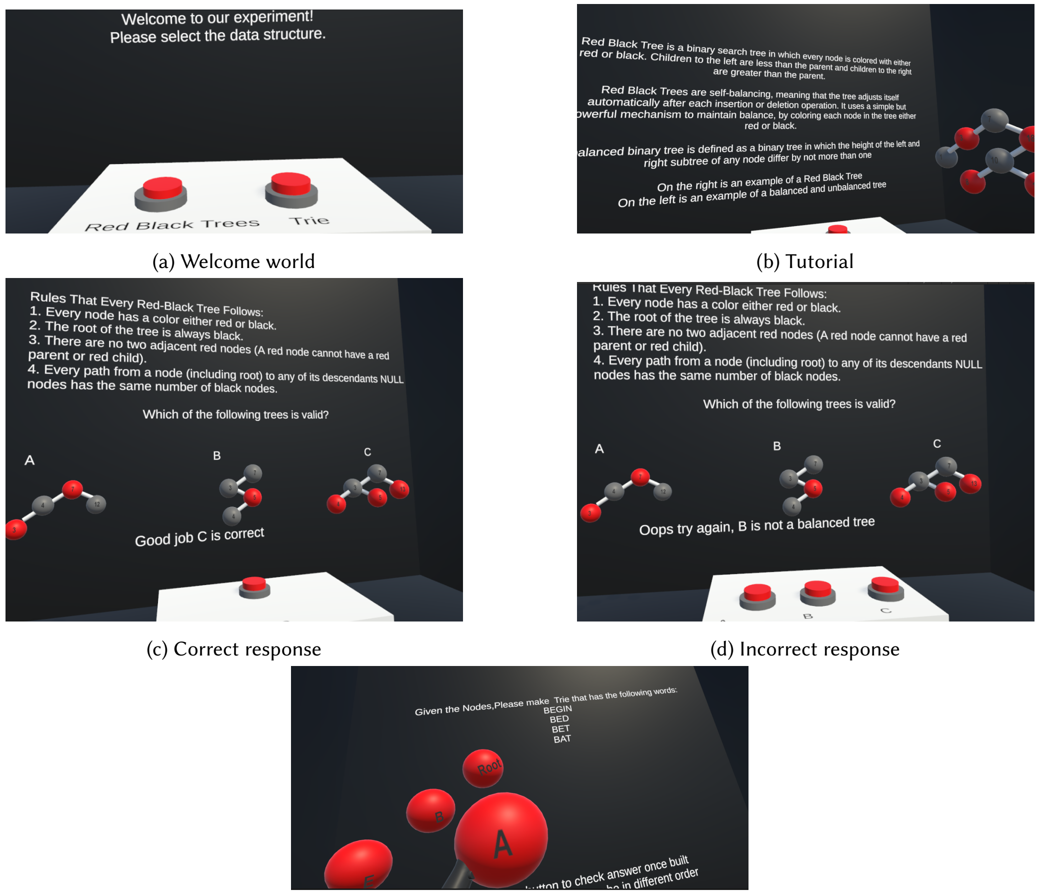
Participants were be asked to come back three days later, to take a follow up quiz for each data structure to test their learning retention. From here they took take an exit survey asking which experience they like better, and for other feed back on the experience. Finally the participants were debriefed on the experiment and asked if they had any questions about the experiment.

3.2 Control

The control portion asked participants to complete an online reading that presented them with an overview of their assigned data structure. Both readings were the introductory articles produced by the GeeksforGeeks website for Red-Black trees [12] and Trie [13]. These articles were chosen as the GeeksforGeeks website is prevalent resource for learning computer science topics as well as being the only resources that provided an article on both Trie and Red-Black trees. The shared formatting and contents of the articles is meant to reduce confounding variables.

3.3 VR Application

The VR application was built using Unity. The participants were put in a welcome world, and they selected the structure they are meant to learn by selecting the respective button. From here the students went through a tutorial scene where there was an example, and explanations on how each data structure works. Once the participant has completed this tutorial, they move on to a number of question scenes, where they answered questions about the data structure, while having examples in front of them. After they completed the training scenes, they then went to a 'free play' world where they could build their data structure, based on the prompt given. They were provided with the nodes that were needed to complete the tree. They spent the level building the tree. Once they were satisfied with their solution, they then could check their answer against a given solution. If they were wrong they could go back and fix their solution, if they were



(a) Welcome world

(b) Tutorial

(c) Correct response

(d) Incorrect response

(e) Free play

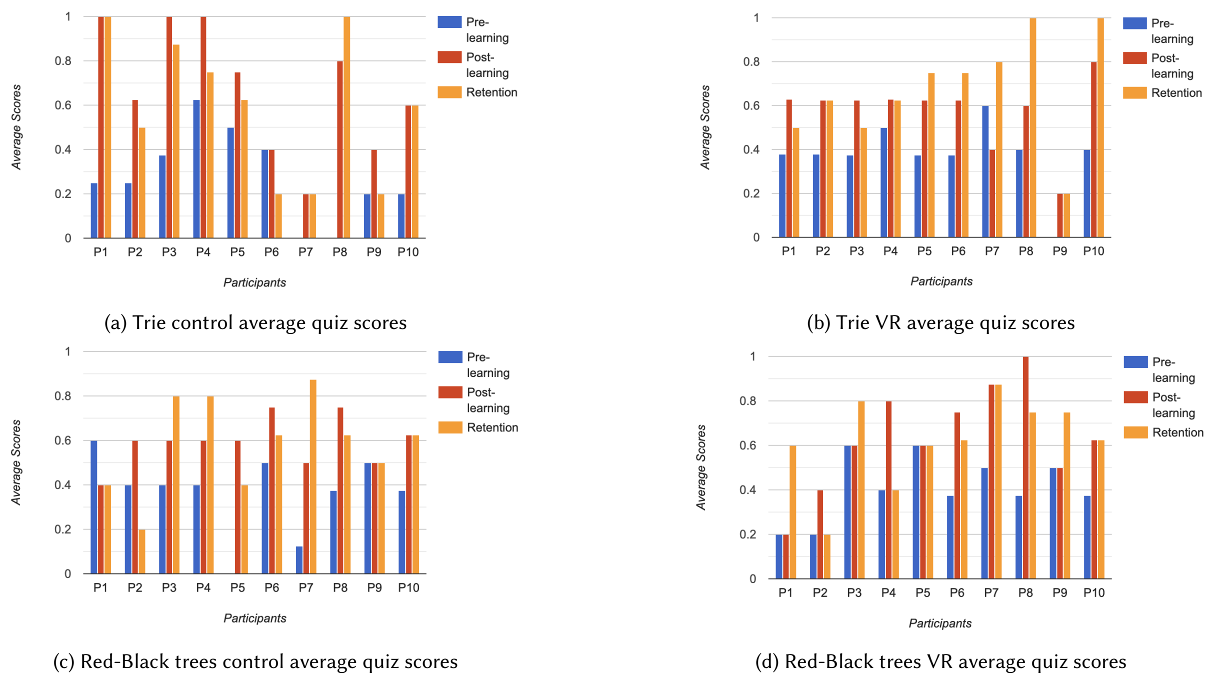
Fig. 1. Examples of VR experience

correct they would exit the experiment. Examples of the VR experience could be seen in Fig 1. This includes examples of how questions were laid out, and the free play experience.

4 RESULTS

4.1 Overview

Figure 2 shows the pre-learning, post-learning and retention scores for each participant as a percentage. Each of the two groups had ten participants. Since this study was conducted within-subjects the same participants that were in the Red-Black VR Group 2d were also in the Trie Control Group 2a. Likewise, the participants that were in the Trie VR 2b were also in the Red-Black Control 2c.



(a) Trie control average quiz scores

(b) Trie VR average quiz scores

(c) Red-Black trees control average quiz scores

(d) Red-Black trees VR average quiz scores

Fig. 2. Quiz Scores

4.2 VR All vs Control All

This section looks at the data from all participants from the VR modules group and all participants from the control module group. Table 1 and 2 show the results of the ANOVA test for both of these groups.

4.2.1 Score Difference Pre-Learning to Post-Learning (SDPP). This section shows the score difference pre-learning to post-learning. This was calculated was by taking the post-learning score for each participant and subtracting the pre-learning score from it. This gave us a column of differences in scores for both the VR and the control modules. We then ran an ANOVA test to see if there was any statistical difference in the VR differences vs the control differences. The results are shown in Table 1.

Groups	Count	Sum	Average	Variance
Diff VR	20	4.95	.2475	.06604
Diff CON	20	5.9	.295	.06714

(a) Summary Control vs VR

Source Var	SS	df	MS	F	P-value	F crit
Between	.0226	1	0.0226	0.3388	0.564	4.0981
Within	2.5306	38	.0576			
Total	2.5532	39				

(b) ANOVA Control vs VR

Table 1. Control vs VR (Pre-Learning to Post-Learning)

4.2.2 Score Difference Post-Learning to Retention-Learning (SDPR). This section shows the score difference post-learning to retention-learning. This was calculated in a similar way from the previous section by taking the retention-learning score for each participant and subtracting the post-learning score from it. This gives us a column of differences in scores for both the VR and the control modules. We then ran an ANOVA test to see if there was any statistical difference in the VR differences vs the control differences. The results are shown in Table 2.

Groups	Count	Sum	Average	Variance
Diff VR	20	0.15	.0075	.0688
Diff CON	20	-0.775	-0.0388	.03345

(a) Summary Control vs VR

Source Var	SS	df	MS	F	P-value	F crit
Between	0.0214	1	.0214	.4186	.5215	4.0981
Within	1.9419	38	.0511			
Total	1.9633	39				

(b) ANOVA Control vs VR

Table 2. Control vs VR (Post-Learning to Retention-Learning)

4.3 VR Red-Black vs Control Red-Black

This section looks at the data from participants in the VR Red-Black group and the control Red-Black group. Table 3 and 4 show the results of the ANOVA test for both of these groups.

4.3.1 Score Difference Pre-Learning to Post-Learning (SDPP). This section shows the score difference pre-learning to post-learning in the Red-Black Groups. This was calculated the same way as the SDPP subsection in section 4.2. The results are shown in Table 3.

Groups	Count	Sum	Average	Variance
Diff VR	10	2.225	.2225	.0488
Diff CON	10	1.925	.1925	.0520

(a) Summary Control vs VR

Source Var	SS	df	MS	F	P-value	F crit
Between	0.0045	1	.0045	.0891	.7686	4.4138
Within	0.9081	18	.0504			
Total	0.9126	19				

(b) ANOVA Control vs VR

Table 3. Control vs VR Red-Black Trees (Pre-Learning to Post-Learning)

4.3.2 Score Difference Post-Learning to Retention-Learning (SDPR). This section shows the score difference post-learning to retention-learning in the Red-Black groups. This was calculated the same way as the SDPR subsection in section 4.2. The results are shown in Table 4.

Groups	Count	Sum	Average	Variance
Diff VR	10	-0.125	-0.0125	.0598
Diff CON	10	.0500	.0050	.04844

(a) Summary Control vs VR

Source Var	SS	df	MS	F	P-value	F crit
Between	.00153	1	.00153	.0282	.8683	4.4138
Within	.9750	18	.0541			
Total	0.9765	19				

(b) ANOVA Control vs VR

Table 4. Control vs VR Red-Black Tree (Post-Learning to Retention-Learning)

4.4 VR Trie vs Control Trie

4.4.1 Score Difference Pre-Learning to Post-Learning (SDPP). This section shows the score difference pre-learning to post-learning for the Trie Groups. This was calculated the same way as the SDPP subsection in section 4.2. The results are shown in table 5.

Groups	Count	Sum	Average	Variance
Diff VR	10	2.73	.2725	.0892
Diff CON	10	3.98	.3975	.0663

(a) Summary Control vs VR

Source Var	SS	df	MS	F	P-value	F crit
Between	.0781	1	1.0045	.3295	0.564	4.4139
Within	1.3998	18	0.0777			
Total	1.478	19				

(b) ANOVA Control vs VR

Table 5. Control vs VR Trie (Pre-Learning to Post-Learning)

4.4.2 Score Difference Post-Learning to Retention-Learning (SDPR). This section shows the score difference post-learning to retention-learning for the Trie Groups. This was calculated the same way as the SDPR subsection in section 4.2. The results are shown in table 6.

Groups	Count	Sum	Average	Variance
Diff VR	10	.275	.0275	.0844
Diff CON	10	-0.825	-0.0825	.0179

(a) Summary Control vs VR

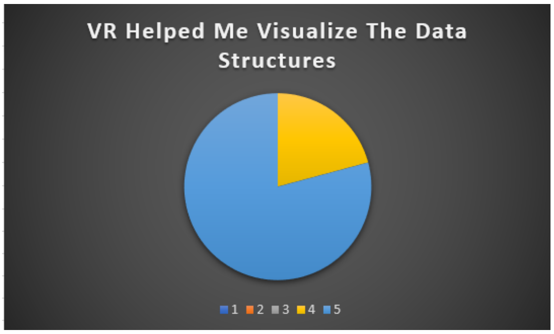
Source Var	SS	df	MS	F	P-value	F crit
Between	0.0605	1	.06050	1.1828	.2911	4.4139
Within	0.9206	18	.0511			
Total	0.9811	19				

(b) ANOVA Control vs VR

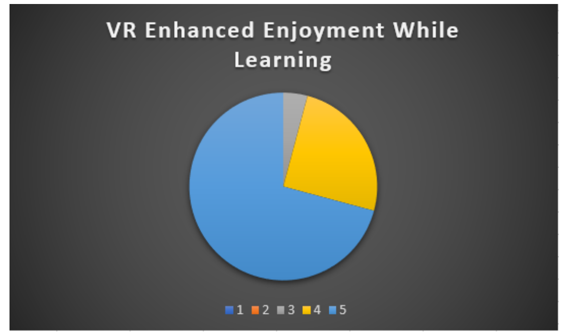
Table 6. Control vs VR Trie (Post-Learning to Retention-Learning)

4.5 Survey Results

These are the results of a few of the survey questions we asked participants after the study was completed. Figure 3a shows a pie chart of the survey results for VR helping the participant visualize the data structures. The possible answers ranged from one to five, one being strongly disagree and five being strongly agree. Figure 3b shows a pie chart of the survey results for VR enhancing enjoyment while learning. The possible answer ranges and meanings are the exact same as the previous figure.



(a) Help In Visualization Reported



(b) Enjoyment Enhancement Reported

Fig. 3. Survey Results

5 DISCUSSION

5.1 Quiz Scores

The quiz scores showed great promise for the VR modules when it came to retention. Both the VR Red-Black group and the VR Trie group had a higher retention-score average than their control counterparts by about 5%. The pre-learning score was also higher for both VR modules, but since this measurement was taken before any actual learning had occurred this was likely due to chance.

5.2 All VR vs All Control

With both VR modules compared against both control modules, the results were not statistically significant for the SDPP and the SDPR tests. For the SDPP test, the control had a higher score difference by about .5. This means that subjects in the control learned more after completing the control module and performed better on the post learning test than subjects from the VR module.

For the SDPR test, the VR modules actually had a net-positive score difference. This means that on average subjects performed better on the retention test than they did on the post-learning test. Despite the difference between the VR and the control modules only 3 percent, this statistic could imply that VR modules help increase learning retention. Unfortunately, the SDPP p-value was .564 and the SDPR p-value was .5215. Because of this, we must accept the null hypothesis which is VR does not lead to a higher SDPP nor a higher SDPR when compared to the control moduels.

5.3 Red-Black VR vs Red-Black Control

For the Red-Black test the results were similar. For the SDPP test, the VR module did have a higher average score difference by about 3 percent. This could indicate a slight improvement in learning performance for the VR module compared to the control module.

For the SDPR test, the averages were very similar. The control did have a net positive difference for this test but the overall difference between the VR and the control module was only about .4%. Since both p-values were over the .05 thresh hold, we must accept the null hypothesis which states In the Red-Black group, the VR module did not lead to a higher SDPP nor a higher SDPR when compared to the control.

5.4 Trie VR vs Trie Control

For the Trie modules the results were mixed. The SDPP average for the VR module was about 27% compared to 39% for the control. The control also had a lower variance than the VR module as well.

For the SDPR, the VR module had a positive score once again. This means that on average the participants scored higher on the retention test than the post-learning test for the VR module. The overall difference between the VR and the control module was nearly 4%. Nevertheless, both p-values were over the .05 threshold which means that we must accept the null hypothesis. In the Trie group, the VR module did not lead to a higher SDPP nor a higher SDPR when compared to the control.

5.5 Survey

The survey results were the most promising. 100% of participants either strongly agreed or agreed that VR helped them visualize the data structures. This is the overall goal of a VR learning module; to improve visualization of complex topics.

On top of this, more than 90% of participants either strongly agreed or agreed that VR enhanced enjoyment while learning. If a learning module is able to produce the same results while being more enjoyable than it is a superior learning platform. This is because there is the potential to reduce burnout which is a phenomenon that is highly detrimental to learning according to these studies [1] [17] [29]

6 FUTURE WORKS

While this study provides insight of the use of VR applications in education, there are some limitations to the study. The number of different topics being taught was extremely limited. Only Tries, and Red-Black trees were taught. Future studies could expand on this and teach different structures, or more fundamental concepts such as if statements, for loops, and arrays. Santiago Bolivar et al. created a prototype around these concepts and saw great success with it [what does this mean] [25]. Expanding the number of topics being taught may help give more insight in this area.

The prototype of this study had a more limited interactive environment, a single level that allowed the user to work with everything they had learned. Participants liked this level as seen in Fig 3. Expanding this interactive environment to give better feed back to the student, and having more of them may have an impact on students learning.

The prototype's black background was not the most friendly environment for the student to learn in. Exploring if the background of the environment that the student is in has in impact on the learning or retention of the topic would be an interesting finding. This knowledge could help the VR learning medium in general.

In the feedback about the study from the participants, one theme was clear, they really enjoyed the VR experience. This could be because of a multitude of reasons, perhaps VR is novel, or the interaction allowed them to feel more in control. Exploring why this is could give some in site on how humans learn. Expanding on this work, it would be interesting to see if the enjoyment of the learning would lead to high engagement in the material. Students may not learn better from this medium, but they may want to learn more, or be more excited to learn from this medium. Existing work from Fong-Ling already show that gamified learning can lead to high quiz results [10].

7 CONCLUSION

Overall this experiment did not show statistically significant results on virtual reality leading to a higher learning or retention rate than compared to the control counterparts.

That does not mean that there is nothing to take away from this experiment however. As mentioned in 5.1, The retention score for the VR modules was actually higher than the post-learning score. This could mean that VR is more engaging over time and follow up studies could provide more concrete evidence to back this up.

On top of this, the survey data was overwhelmingly positive. 100% of participants agreed or strongly agreed that VR helped them visualize the data structures and 95% of participants agreed or strongly agreed that VR enhanced their learning experience. Since the learning and retention rate were fairly similar between the control and the VR modules, these survey results could indicate that VR enhances learning enjoyment while not sacrificing statistical results. Much like the study that looked at game based learning with civil engineering [22] introducing a "joy" metric or how much someone enjoyed the learning experience is really where we can tell these two modules apart. Even though the statistical data did not show conclusive results for our VR modules. It is still entirely possible for VR to be superior to traditional learning in other metrics.

REFERENCES

[1] Tariq Mehmood Bhuttah Xuqun You Abaid Ur Rehman. 2022. Linking Burnout to Psychological Well-being: The Mediating Role of Social Support and Learning Motivation. *Psychology Research and Behavior Management* 13, 1 (2022), 545–554. https://doi.org/10.2147/PRBM.S250961 arXiv:https://www.tandfonline.com/doi/full/10.2147/PRBM.S250961

[2] Lahijan Branch Abbas Pourhossein Gilakjani. 2012. Visual, Auditory, Kinaesthetic Learning Styles and Their Impacts on English Language Teaching. *Journal of Studies in Education* 2, 1 (2012), 104–113. https://doi.org/10.5296/jse.v2i1.1007 arXiv:https://d1wqtxts1xzle7.cloudfront.net/50341580/Visual-Auditory-Kinaesthetic–libre.pdf

[3] Vartika Agrahari and Sridhar Chimalakonda. 2020. AST[AR] â Towards Using Augmented Reality and Abstract Syntax Trees for Teaching Data Structures To Novice Programmers. In *2020 IEEE 20th International Conference on Advanced Learning Technologies (ICALT)*. 311–315. https://doi.org/10.1109/ICALT49669.2020.00100

[4] Jenny Barker and Peter Gossman. 2013. The learning impact of a virtual learning environment: studentsâ views. *Teacher Education Advancement Network Journal (TEAN)* 5 (2013), 19â38. https://insight.cumbria.ac.uk/id/eprint/1455/

[5] M.B. McGrath; J.R. Brown. 2005. Visual learning for science and engineering. *The Clearing House* 25, 5 (2005), 56 – 63. https://doi.org/10.1109/MCG.2005.117 arXiv:https://ieeexplore.ieee.org/abstract/document/1510540

[6] Benjamin A. Clegg, Dellapaolera, Dubey, Thrash, Kapadia, Hoelscher, Schinazi, Johanesen, Sun, Nembhard, and et al. 2022. Multimedia and immersive training materials influence impressions of learning but not learning outcomes. https://par.nsf.gov/biblio/10357475

[7] Stephen Cooper, Wanda Dann, and Randy Pausch. 2000. Alice: A 3-D Tool for Introductory Programming Concepts. *J. Comput. Sci. Coll.* 15, 5 (apr 2000), 107â116.

[8] Athanasios Drigas, Eleni Mitsea, and Charalabos Skianis. 2022. Virtual Reality and Metacognition Training Techniques for Learning Disabilities. *Sustainability* 14, 16 (2022). https://doi.org/10.3390/su141610170

[9] Karen Burke Rita Dunn. 2010. Learning Style-Based Teaching to Raise Minority Student Test Scores There's No Debate! *The Clearing House* 76, 2 (2010), 103–106. https://doi.org/10.1080/00098650209604959 arXiv:https://www.tandfonline.com/doi/abs/10.1080/00098650209604959

[10] Sheng-Chin Yu Fong-Ling Fu a, Rong-Chang Su a. 2007. EGameFlow: A scale to measure learnersâ enjoyment of e-learning games. *Science Direct* 52, 1 (2007), 101–112. https://doi.org/10.1016/j.compedu.2008.07.004 arXiv:https://www.sciencedirect.com/science/article/abs/pii/S0360131508001024

[11] Laura Freina and Michela Ott. 2014. A literature review on immersive virtual reality in education ... - CNR. https://www.itd.cnr.it/download/eLSE/202015/20Freina/20Ott/20Paper.pdf

[12] GeeksforGeeks. 2023. Introduction to red-black tree. https://www.geeksforgeeks.org/introduction-to-red-black-tree/

[13] GeeksforGeeks. 2023. Trie: (insert and search). https://www.geeksforgeeks.org/trie-insert-and-search/

[14] Chelsea Gordon, Roman Lysecky, and Frank Vahid. 2021. The shift from static college textbooks to customizable content: A case study at zyBooks. In *2021 IEEE Frontiers in Education Conference (FIE)*. 1–7. https://doi.org/10.1109/FIE49875.2021.9637289

[15] Sandra Helsel. 1992. Virtual Reality and Education. *Educational Technology* 32, 5 (1992), 38–42. http://www.jstor.org/stable/44425644

[16] Chris Kolmar. 2023. 25+ AMAZING VIRTUAL REALITY STATISTICS [2023]: THE FUTURE OF VR + AR. https://www.zippia.com/advice/virtual-reality-statistics/

[17] Ruoyun Yin Lei Tang, Fan Zhang* and Zhaoya Fan. 2021. Effect of Interventions on Learning Burnout: A Systematic Review and Meta-Analysis. *Frontiers in Psychology* 12, 1 (2021), 104–113. https://doi.org/10.3389/fpsyg.2021.645662 arXiv:https://www.frontiersin.org/articles/10.3389/fpsyg.2021.645662/full

[18] Fengxia Li, Dongni Li, Jun Zheng, and Sanyuan Zhao. 2015. Virtual experiments for introduction of computing: Using virtual reality technology. In *2015 IEEE Frontiers in Education Conference (FIE)*. 1–5. https://doi.org/10.1109/FIE.2015.7344376

[19] S. V. Lomov, T. Mikolanda, M. Kosek, and I. Verpoest. 2007. Model of internal geometry of textile fabrics: Data structure and virtual reality implementation. *The Journal of The Textile Institute* 98, 1 (2007), 1–13. https://doi.org/10.1533/joti.2006.0251 arXiv:https://doi.org/10.1533/joti.2006.0251

[20] Khadija Mahmoud, Isaac Harris, Husam Yassin, Thomas J. Hurkxkens, Omar K. Matar, Nitesh Bhatia, and Irene Kalkanis. 2020. Does Immersive VR Increase Learning Gain When Compared to a Non-immersive VR Learning Experience?. In *Learning and Collaboration Technologies. Human and Technology Ecosystems*, Panayiotis Zaphiris and Andri Ioannou (Eds.). Springer International Publishing, Cham, 480–498.

[21] Benjy Marks and Jacqueline Thomas. 2021. Adoption of virtual reality technology in Higher Education: An evaluation of five teaching semesters in a purpose-designed laboratory - education and information technologies. https://link.springer.com/article/10.1007/s10639-021-10653-6

[22] Andreas Holzinger Martin Ebner a. 2007. Successful implementation of user-centered game based learning in higher education: An example from civil engineering. *Science Direct* 49, 3 (2007), 1–13. https://doi.org/10.1533/joti.2006.0251 arXiv:https://www.sciencedirect.com/science/article/abs/pii/S0360131505001910

[23] Husnu S. Narman, Cameron Berry, Alex Canfield, Logan Carpenter, Jeremy Giese, Neil Loftus, and Isabella Schrader. 2020. Augmented Reality for Teaching Data Structures in Computer Science. In *2020 IEEE Global Humanitarian Technology Conference (GHTC)*. 1–7. https://doi.org/10.1109/GHTC46280.2020.9342932

[24] Rand J. Spiro Paul J. Feltovich, Richard L. Coulson. 2001. Learnersâ (mis) Understanding of Important and Difficult Concepts: A Challenge to Smart Machines in Education. https://www.researchgate.net/profile/Richard-Coulson/publication/234818797_Learners'_misunderstanding_of_important_and_difficult_concepts_a_challenge_to_smart_machines_in_education/links/5658ca6f08ae1ef9297e03f9/Learners-misunderstanding-of-important-and-difficult-concepts-a-challenge-to-smart-machines-in-education.pdf

[25] Armando Carrasquillo Adam S. Williams-Naphtali D. Rishe Francisco R. Ortega Santiago Bolivar, Daniel Perez. 2019. 3D Interaction for Computer Science Educational VR Game. *Universal Access in Human-Computer Interaction. Theory, Methods and Tools* 11572, 1 (2019), 408–419. https://doi.org/10.1007/978-3-030-23560-4_30 arXiv:https://link.springer.com/chapter/10.1007/978-3-030-23560-$4_3$0

[26] Dorothy Strickland. 1996. Brief Report: Two Case Studies Using Virtual Reality as a Learning Tool for Autistic Children. https://do2learn.com/aboutus/research/briefreport.htm

[27] Nehi Tuli. 2020. Experience Flemingâs rule in Electromagnetism Using Augmented Reality: Analyzing Impact on Students Learning. https://www.sciencedirect.com/science/article/pii/S1877050920314150

[28] Martin Weller. 2018. Twenty years of Edtech. https://er.educause.edu/articles/2018/7/twenty-years-of-edtech

[29] Hui Zhang Aihong Chen Yun Luo, Zhenhong Wang. 2016. The Influence of Family Socio-economic Status on Learning Burnout in Adolescents: Mediating and Moderating Effects. *Journal of Child and Family Studies* 25, 1 (2016), 2111â2119. https://doi.org/10.1007/s10826-016-0400-2 arXiv:https://link.springer.com/article/10.1007/s10826-016-0400-2

Received 14 April 2023; revised 14 April 2023; accepted 14 April 2023