Computer Science Education meets Virtual Reality: GNN-3D-Tutor

RONALDO CANIZALES, Colorado State University, United States

GNN-3D-Tutor aims to lower the steep learning curve of Graph Neural Networks (GNNs) and Graph Representation Learning (GRL) while exploring the use of Virtual Reality (VR) in Computer Science Education (CSEdu) through a quantitative study that measures, compares, and analyzes test results and qualitative feedback of participants exposed to either traditional lecture-based or experimental VR-based learning materials; supported by the "notional machine" pedagogic practice of the constructivism theory.

CCS Concepts: • **Social and professional topics → Computer science education**; • **Human-centered computing → Human computer interaction (HCI)**; • **Computing methodologies → Neural networks**.

Additional Key Words and Phrases: Virtual Reality, Head-mounted display, Graph Representation Learning, STEM Education

ACM Reference Format:
Ronaldo Canizales. 2023. Computer Science Education meets Virtual Reality: GNN-3D-Tutor. In *Fall 2023 Project, December 10, 2023, Fort Collins, CO.* ACM, New York, NY, USA, 8 pages. https://doi.org/XXXXXXX.XXXXXXX

1 INTRODUCTION

A fascinating research area that is currently at an early age is the use of Virtual Reality (VR) in Computer Science Education (CSEdu) [15]. Currently, there are no well-defined steps for integrating technologies like VR in CSEdu that improve learning outcomes in a reliable and generalizable manner [3]. Most recent attempts focus on introductory computer science concepts, but only a handful are related to advanced topics [2].

Graph Neural Networks (GNNs) are currently used in numerous real-world scenarios like computer vision, data mining, natural language processing, recommendation systems, anomaly detection, and others [16]. Unlike text and images, whose semantic meaning is simple and straightforward, graphs are less intuitive. Hence, understanding and explaining deep graph models is a non-trivial, important, and challenging task [18].

The pedagogic theory used as a baseline for this project is constructivism, which states that learning concepts and skills through exploration guided by an instructor is better than explicitly telling students everything they need to know, as is common in more direct instruction [11]. The pedagogical practice that will guide the building of the tool content is the so-called Notional Machine, defined as knowledge of the general properties of the machine that one is learning to control [6]. Making the notional machine explicit in the learning process leads to misconceptions or fragile knowledge. An example of this is when people tend to attribute human reasoning to computers and AI models.

Visualizations have been proposed by CSEdu researchers as a mechanism for establishing a mental model of notional machines [6]. From the point of view of Cognitive constructivism, Algorithm Visualizations (AV) are seen as educationally effective [9].

Manuscript submitted to ACM

2 RELATED WORK

Recent surveys about the use of VR in CSEdu to support teaching, training, and learning show that interest has grown in the last decade. Pirker et al. [15] identify the main advantages of VR as engagement, playfulness, visualizations, collaboration, content as a metaphor, and learner's experience content. Agbdo et al. [2] found that the most commonly used sample size fell between 11-20 participants, questionaries (46%) remain the most used tool for data collection, descriptive analysis is the most preferred data analysis method, and that quantitative studies dominate in terms of research methodology. Regarding Mixed Reality technology in STEM Education, Batista et al. [3] state that investigation is the most common instructional technique (76%) over games and observation.

Related to immersive VR applications in K-12 education, Pellas et al. [12][13] point out some challenges, like 3D user interfaces not always being intuitive and equipment availability restrictions allowing only six to seven students concurrently. They also report positive benefits of using VR, like increased student motivation, self-efficacy, attention to learning by doing experimental tasks, engagement in collaborative tasks, and positive attitude about learning.

VR learning activities are interesting and welcomed by the engineering education community, according to Huang and Roscoe [8]; they claim that most users had a positive attitude toward VR learning and provided helpful feedback to VR applications that were in the development stage. Lastly, 360-degree videos have a wide variety of educational potential, claim Parker et al. [14]; they state that live-learning experience in the classroom is still scarce, and 360-degree videos can provide immersive educational experiences of otherwise not accessible real-world environments.

The two papers more closely related to this project regarding the experimental procedure are [7] and [1], where 44 and 47 CS undergraduate students were randomly divided into experimental and control groups and received different learning materials about the same topic, as shown in Figure 1 left. Both studies aim to examine the efficiency and motivation of a VR learning environment vs. a traditional lecture-based approach. Both studies used quantitative data analysis methods to compare pre-test and post-test results, like ANOVA and t-test, and a final qualitative questionnaire asking opinions towards the usability of the VR tool.

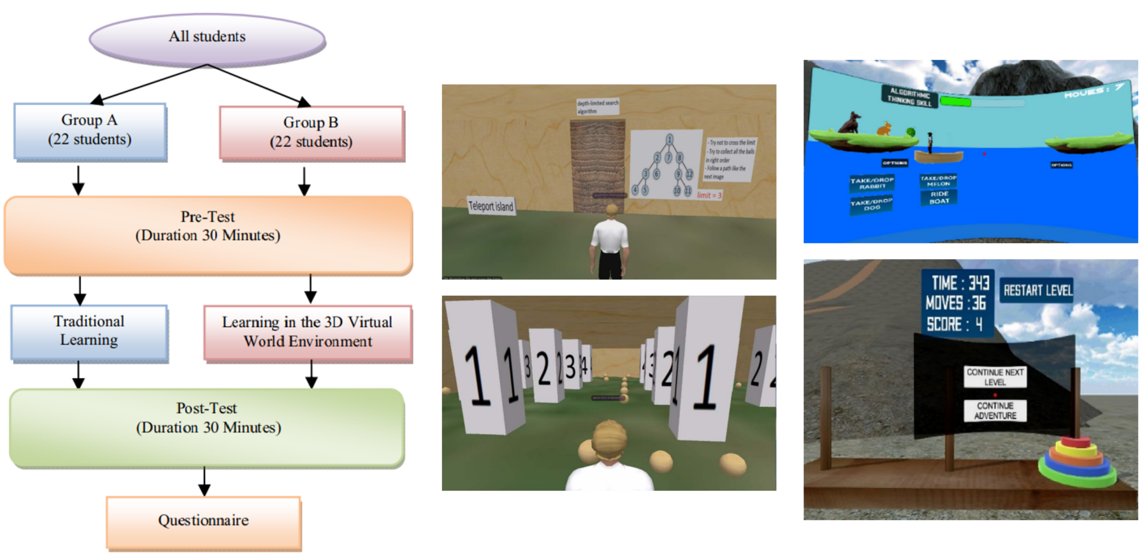

Fig. 1. Left: Experimental phases in [7]. Center: Virtual world environment [7]. Right: Mini games [1].

The aforementioned VR applications content consists of visualizations of algorithms, Figure 1 center, and minigames that support computational thinking (CT), Figure 1 right. Foteini et al. [7] findings suggest that their VR application promotes students' CT competence, as the experimental group demonstrated more problem-solving, algorithmic thinking, problem decomposition, abstraction, pattern recognition, and recursive thinking skills. Visualizing algorithms and utilizing suitable learning activities in terms of students' active engagement improved students' comprehension and learning efficiency, according to Agbo et al. [1]. Also, their results indicate that a VR environment is a very efficient way to increase students' interest, motivation, and knowledge construction.

Another VR-based learning material, Lord of Secure [17], claims to be the first learning tool focused on cyber security based on VR. It does not use a control group with lecture-based learning. It only has one experimental group and uses pre and post-tests on each content chapter.

A VR-based tool that supports teaching the abstract concept of Finite State Machines is discussed by [5]. The authors state that CSEdu needs new ways of explaining and learning concepts. It does not experiment with any cohort or evaluate with actual students. Similar to the previous one, [4] proposes a VR-based tool dressed as an escape room that teaches CS concepts through small challenges, such as if statements, arrays, and loops. However, it focuses on the design and implementation and does not mention the evaluation of the tool on actual students.

3 METHODS

The methodology followed in this project consists of four steps. The first step is to select a topic, Introduction to Graph Machine Learning, and the sample's criteria. All participants must meet two conditions: (a) STEM major senior undergrad, bachelor, or graduate student and (b) proficient reading and writing English skills.

The second step is to create the learning material. (a) A slideshow about the basics of Graph Neural Networks, as seen in Figure 2 left; the content is based on the publicly available Stanford course CS224W: Machine Learning with Graphs lectures by Jure Leskovec [10]. (b) Pre and post-test questionaries, of 15 and 20 questions, respectively, using Google Forms as shown in Figure 2 center. (c) Lecture-like videos explaining the content. Two videos were recorded, one in English and one in Spanish, Figure 2 right; the content, length, and lecturer remained the same.

Fig. 2. Left: Content slides (link). Center: pre (link) and post-test (link). Right: Lecture English (link) and Spanish (link) videos.

The third step consists of designing and implementing a VR-based learning material with the same content as the lecture slides; this was done using Unity 2021 and the VR headset Meta Quest 2. Figure 3 shows the mapping between classrooms and subsections of the lecture. The content is presented on all the walls in a clockwise manner.

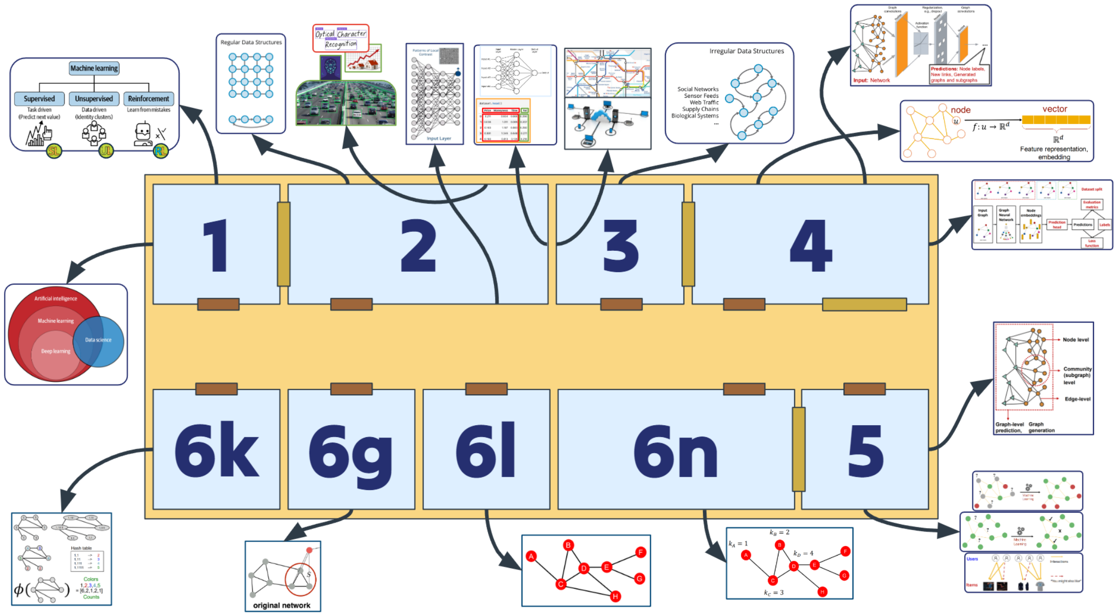

Fig. 3. GNN-3D-Tutor's diagram. Unity's model maps a lecture's content to VR; each slide's content is assigned to a wall.

The implementation process can be seen in Figure 4. It consists of four stages: (1) creation of ground, walls, doors, and windows; (2) addition of static content, such as buttons that show images and portions of slides; (3) addition of dynamic content, such as interactive examples and exercises to all algorithms covered in the material, and (4) addition of decorative assets such as doors, six kinds of flower pots, bookshelves, chairs, and announcement boards.

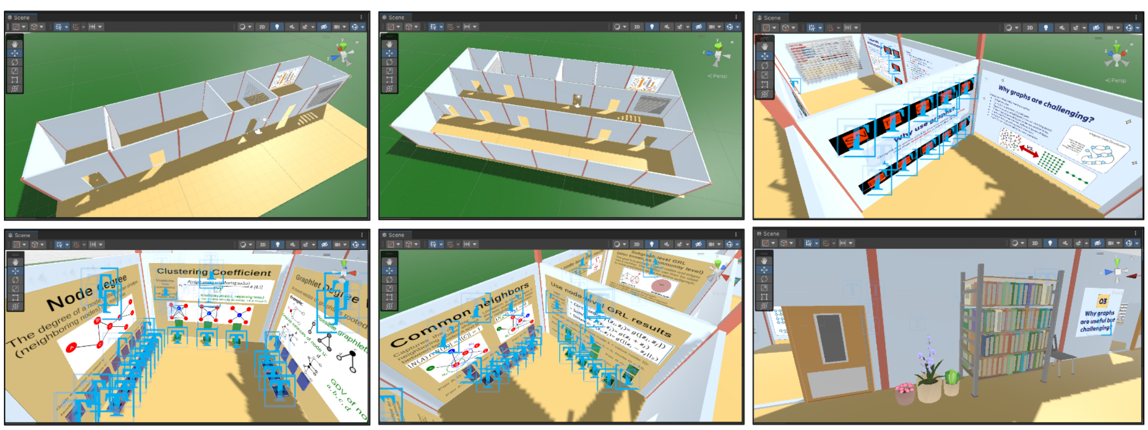

Fig. 4. Implementation of the VR application: walls, static content, interactive activities, and final decoration.

Lastly, the fourth step is redacting a two-page-long Participant Informed Consent Form, following the guidelines of Colorado State University. The final consent form is available in the annexes section of this document.

3.1 Data collection

After carefully reading the consent form and obtaining a sign from each participant, the pre-test and post-test will be answered by the volunteers at the experiment's beginning and end. Participants will be randomly separated into two groups: (a) control, which will watch a lecture video using a slideshow, and (b) experimental, Figure 5, which will use the Meta Quest 2 VR headset and be exposed to the same content but in a fully immersive virtual reality environment.

Fig. 5. GNN-3D-Tutor's experimental group participants: volunteering CSU STEM majors students.

Conceptual and procedural knowledge types will be measured [9] in the aforementioned pre and post-tests. The former relates to the understanding of the abstract properties of an algorithm, like complexity; the latter relates to the step-by-step behavior of an algorithm, that is, how it operates on a set of input data [9]. It is important to mention that this is a pilot study; thus, the validity of the instruments is not guaranteed, from a pedagogical point of view.

3.2 Data analysis

This project's approach is quantitative. It seeks to find statistically significant differences between participants' pre and post-test grades in both control and experimental groups using a two-sample t-test and/or Mann-Whitney U Test.

- Independent Variable (IV). Comparing traditional vs. VR-based learning resources: IV = learning resource; levels = "traditional" lecture / interactive VR-based content.
- Dependent Variables (DVs). Pre and post-test, examining different levels of Bloom's Taxonomy:
  - Retention: Grade in a qualitative test about GNNs, asking the student to explain how GNNs work.
  - Understanding: Grade in a quantitative test about GNNs, asking the student to perform simple calculations.

The inferential tests this study performs are the comparison between two groups with a between-subjects IV where the H_0 is that sample means are the same. In other words, H_0 says that there is no effect in the sample. H_1, as we know, says that there is an effect. In each case, if we reject H_0, we can conclude, with some confidence, that H_1 is correct. But if we fail to reject H_0, we can not conclude that H_0 is true. Please read section 6.4.3 of [6] for a detailed explanation.

Finally, Cohen's effect size will be obtained to quantify the difference between VR-based and lecture-based learning.

4 RESULTS

Between November 30th and December 6th, thirteen volunteers participated in the study: six in the control group and seven in the experimental group. A summary of all quantitative results can be found in Table 1. According to the Informed Consent Form, all identifiable data (e.g., names) has been replaced with a code only the researcher can access.

Table 1. Pre and post-tests results, R = Retention (qualitative questions), U = Understanding (quantitative questions).

Group	Participant	Pre-test R	Post-test R	Post-test U	Post-test R+U
Control	C01	5.55	11.5	6	17.5
	C02	6.5	12	7	19
	C03	8.25	9.25	2	11.25
	C04	6.75	11	7	18
	C05	6	7	6	13
	C06	3.5	11.75	6	17.75
Experimental	E01	7	11	5	16
	E02	2.5	11.75	4	15.75
	E03	3.25	9.25	5	14.25
	E04	9	10	7	17
	E05	7	12	5	17
	E06	5.5	12	5	17
	E07	8	11.75	5	16.75

Before conducting two-sample t-tests, it is necessary to determine if the control and experimental groups have the same variance. If the ratio between them is less than 4:1, then we can consider them to have equal variance, as shown in Table 2. Thus, t-tests can be applied to compare Retention questions (Pre-test R and Post-test R), and non-parametric Mann-Whitney U tests can be used to compare the remaining (Post-test U and Post-test R+U).

Table 2. Variances and their ratio among control and experimental groups, across different tests.

Variances	Pre-test R	Post-test R	Post-test U	Post-test R+U
Control	2.46	3.77	3.47	9.97
Experimental	5.84	1.18	0.81	1.04
Ratio	1 : 2.4	3.2 : 1	4.3 : 1	9.6 : 1
Applied test	T-test	T-test	M-W U test	M-W U test

4.1 Pre-test: control vs. experimental

According to the t-test results, we fail to reject H_0. There is no statistically significant difference between pre-tests among control and experimental groups. This means that all participants had more or less the same previous knowledge about Graph Machine Learning.

- **Pre-test Retention.** The t-value is 0.04848. The result is not significant, with p-value = 0.9622 $<$ 0.05.

4.2 Post-test: control vs. experimental

According to the t-test and Mann-Whitney U test results, we fail to reject H_0. There is no statistically significant difference between post-tests among control and experimental groups. This means that both learning materials, lecture-based and VR-based, had more or less the same pedagogical effectiveness in the sample.

- **Post-test Retention.** The t-value is -0.80818. The result is not significant, with p-value = 0.436116 $<$ 0.05.
- **Post-test Understanding.** The z-score is -1.3571. The result is not significant, with p-value = 0.1738 $<$ 0.05.
- **Full Post-test.** The z-score is -0.92857. The result is not significant, with p-value = 0.35238 $<$ 0.05.

The previous finding is confirmed through the calculation of Cohen's effect size, which is close to zero. This means that neither level of the Independent Variable was superior to the other. This is good news; using a VR-based version of the content did not negatively affect the grades of the participants.

- **Full Post-test.** Cohen's $d = (16.25 - 16.08)/2.347978 = 0.072403$.

Regarding the educative experience in general, it can be argued that using VR was positive, even though grades were similar between groups. This qualitative argument will be extended in the discussion.

4.3 Participant's end-to-end learning: pre-test vs. post-test

Lastly, regarding pre and post-test scores, H_0 can be successfully rejected. Thus, it can be concluded with 99%+ confidence that H_1 is correct (that the sample means are not equal). This means that being exposed to any learning material, either lecture-based or VR-based, had an effect on the sample. Both parametric and non-parametric results are as follows:

- **Pre vs. post-tests.** The t-value is -6.82539. The result is significant with a p-value < 0.01.
- **Pre vs. post-tests.** The z-score is -4.10256. The result is significant with a p-value < 0.01.

5 DISCUSSION

The study did not find statistically significant differences between post-test results among control and experimental groups; thus, there is insufficient evidence to make any inference. The study does not infer that H_0 is false, nor does it infer that H_0 is true. This can be expected due to the limited amount of participants, less than 10 per group. However, there are positive quantitative and qualitative insights that support the positive potential of VR-based learning material:

- **Quantitative insight:** post-test variances were significantly lower for the experimental group than the control group, suggesting a more consistent retention and understanding of the learning material across participants.
- **Qualitative insights:** most experimental group participants engaged vividly with the learning material, showed visible motivation and a positive attitude towards the interactive elements of the VR application, and stated that they enjoyed the experience more than watching a video tutorial with the same content. Half of the control group participants reported that they felt bored while watching the video. Lastly, the VR application contains some minor bugs, which made the experience even more fun for some participants.

Feedback from experimental group participants included a series of suggestions, for example: (1) avoiding too quiet environments by adding background music, (2) using vector-based fonts for all texts would make it easier to read, (3) including more pictures, animations, and interactive elements; (4) granting access to new rooms (opening doors) based on completed activities, and (5) implementing graded tests inside the VR application.

Some limitations of this pilot study that must be considered in future work are: (1) increasing the number of participants; (2) analyzing the validity of the instruments, aka pre and post-test questions; (3) rethinking the sample inclusion criteria, (4) decreasing the study's overall time, and (5) adding some kind of interactive simulation.

6 CONCLUSION

The usage of Virtual Reality in Computer Science Education brings more advantages than disadvantages, such as increased student motivation and engagement towards learning material. There is plenty of room for research and improvement; there is still no definitive answer to the question of how to make a one-size-fits-all learning material.

All participants who interacted with the VR application reported a very positive attitude toward using this technology in education. However, the study did not find statistically significant differences between the grades obtained by exposure to lecture-based vs. VR-based learning material; thus, there is insufficient evidence to make any inference.

VR-based learning material appears to be as effective as traditional lecture-based material, although a larger sample will be required for any related future work. The author of this study firmly believes that, as technology advances, VR will become a commonly used, helpful resource for educators in Computer Science and all STEM majors in the future.

REFERENCES

[1] Friday Joseph Agbo, Sunday Adewale Olaleye, Matt Bower, and Solomon Sunday Oyelere. 2023. Examining the relationships between students' perceptions of technology, pedagogy, and cognition: the case of immersive virtual reality mini games to foster computational thinking in higher education. https://doi.org/10.1186/s40561-023-00233-1

[2] Friday Joseph Agbo, Ismaila Temitayo Sanusi, Solomon Sunday Oyelere, and Jarkko Suhonen. 2021. Application of Virtual Reality in Computer Science Education: A Systemic Review Based on Bibliometric and Content Analysis Methods. https://doi.org/10.3390/educsci11030142

[3] Alex Batista, Marcello Thiry, Rafael Gonçalves, and Anita Fernandes. 2020. Using Technologies as Virtual Environments for Computer Teaching: A Systematic Review. *Informatics in Education* 19 (06 2020), 201–221. https://doi.org/10.15388/infedu.2020.10

[4] Santiago Bolivar, Daniel Perez, Armando Carrasquillo, Adam S. Williams, Naphtali D. Rishe, and Francisco R. Ortega. 2019. 3D Interaction for Computer Science Educational VR Game. In *Universal Access in Human-Computer Interaction. Theory, Methods and Tools*, Margherita Antona and Constantine Stephanidis (Eds.). Springer International Publishing, Cham, 408–419.

[5] Andreas Dengel. 2018. Seeking the Treasures of Theoretical Computer Science Education: Towards Educational Virtual Reality for the Visualization of Finite State Machines. In *2018 IEEE International Conference on Teaching, Assessment, and Learning for Engineering (TALE)*. 1107–1112. https://doi.org/10.1109/TALE.2018.8615288

[6] Sally Fincher, Anthony Robins, Mark Guzdial, Benedict Boulay, Josh Tenenberg, Brian Dorn, Christopher Hundhausen, Robert Mccartney, Laurie Murphy, Paulo Blikstein, Sepi Moghadam, Andrew Ko, Patricia Haden, Lauren Margulieux, Kristin Searle, Briana Morrison, Kerry Shephard, Michael Loui, Maura Borrego, and Niral Shah. 2019. The Cambridge Handbook of Computing Education Research. https://doi.org/10.1017/9781108654555

[7] Foteini Grivokostopoulou, Isidoros Perikos, and Ioannis Hatzilygeroudis. 2016. An Innovative Educational Environment Based on Virtual Reality and Gamification for Learning Search Algorithms. , 110-115 pages. https://doi.org/10.1109/T4E.2016.029

[8] Wen Huang and Rod Roscoe. 2021. Head-mounted display-based virtual reality systems in engineering education: A review of recent research. *Computer Applications in Engineering Education* 29 (02 2021). https://doi.org/10.1002/cae.22393

[9] Christopher Hundhausen, Sarah Douglas, and John Stasko. 2002. A Meta-Study of Algorithm Visualization Effectiveness. *Journal of Visual Languages and Computing* 13 (06 2002), 259–290. https://doi.org/10.1006/jvlc.2002.0237

[10] Jure Leskovec. 2023. CS224W: Machine Learning with Graphs. https://web.stanford.edu/class/cs224w/index.html

[11] Lauren Margulieux, Brian Dorn, and Kristin Searle. 2019. Learning Sciences for Computing Education. , 208-230 pages. https://doi.org/10.1017/9781108654555.009

[12] Nikolaos Pellas, Andreas Dengel, and Athanasios Christopoulos. 2020. A Scoping Review of Immersive Virtual Reality in STEM Education. *IEEE Transactions on Learning Technologies* 13, 4 (2020), 748–761. https://doi.org/10.1109/TLT.2020.3019405

[13] Nikolaos Pellas, Stylianos Mystakidis, and Ioannis Kazanidis. 2021. Immersive Virtual Reality in K-12 and Higher Education: A Systematic Review of the Last Decade Scientific Literature. *Virtual Real.* 25, 3 (sep 2021), 835–861. https://doi.org/10.1007/s10055-020-00489-9

[14] Johanna Pirker and Andreas Dengel. 2021. The Potential of 360° Virtual Reality Videos and Real VR for Education—A Literature Review. *IEEE Computer Graphics and Applications* 41, 4 (2021), 76–89. https://doi.org/10.1109/MCG.2021.3067999

[15] Johanna Pirker, Andreas Dengel, Michael Holly, and Saeed Safikhani. 2020. Virtual Reality in Computer Science Education: A Systematic Review. In *Proceedings of the 26th ACM Symposium on Virtual Reality Software and Technology* (Virtual Event, Canada) *(VRST '20)*. Association for Computing Machinery, New York, NY, USA, Article 8, 8 pages. https://doi.org/10.1145/3385956.3418947

[16] Ryoma Sato. 2020. A Survey on The Expressive Power of Graph Neural Networks. arXiv:2003.04078 [cs.LG]

[17] Vasaka Visoottiviseth, Atit Phungphat, Nuntapob Puttawong, Pamanut Chantaraumporn, and Jason Haga. 2018. Lord of Secure: the Virtual Reality Game for Educating Network Security. In *2018 Seventh ICT International Student Project Conference (ICT-ISPC)*. 1–6. https://doi.org/10.1109/ICT-ISPC.2018.8523947

[18] Hao Yuan, Haiyang Yu, Shurui Gui, and Shuiwang Ji. 2022. Explainability in Graph Neural Networks: A Taxonomic Survey. arXiv:2012.15445 [cs.LG]

7 ANNEXES: ADULT PARTICIPANT INFORMED CONSENT FORM (SEE THE NEXT PAGE)

Received 17 October 2023; revised 17 November 2023; accepted 10 December 2023

ADULT PARTICIPANT INFORMED CONSENT

Project name: GNN-3D-Tutor

PRINCIPAL INVESTIGATOR: Ronaldo Canizales, MS in CS Student, CS Department.

WHAT IS THE PURPOSE OF THIS STUDY?

The purpose of this research study is to compare "traditional" lecture-based learning material vs. "experimental" virtual reality-based learning material. The selected topic is Introduction to Graph Machine Learning.

WHY AM I BEING INVITED TO TAKE PART IN THIS RESEARCH?

You fit this project's sample criteria: (1) STEM major upper undergrad, bachelor, or graduate student; and (2) proficient reading and writing English skills.

WHERE IS THE STUDY GOING TO TAKE PLACE, AND HOW LONG WILL IT LAST?

- Experimental group: In person, using VR. It is up to the participant. It can be either at a convenient location for you or at the International House, 1400 West Elizabeth Street (1 block west of CSU campus). The duration is about 40 minutes.
- Control group: remote, using pre-recorded video. The place is at your convenience. The duration is about 40 minutes.

WHAT WILL I BE ASKED TO DO?

If you volunteer to take part in this study, you will be asked to do the following:

1. Pre-test: Answer a 15-question Google Form about Graph Machine Learning.
2. It will depend on whether you belong to the control or experimental group.
   a. Experimental group: In person. Use a VR headset and freely navigate a virtual classroom with interactive elements.
   b. Control group: remote. Watch a YouTube lecture-like video in your language of preference, Spanish or English.
3. Post-test: Answer a 20-question Google Form about Graph Machine Learning.

The data that must be recorded is all your pre-test and post-test answers. For experimental group participants only, you will be asked at the end of the experiment whether you feel comfortable having taken one to two photos of you using the VR headset or not.

ARE THERE ANY BENEFITS FROM TAKING PART IN THIS STUDY?

There may be no direct benefit to you as a participant in this study. However, we hope you learn more about the basics of Graph Machine Learning, which is a fascinating topic.

WHAT ARE THE POSSIBLE RISKS AND DISCOMFORTS?

While the level of risk is minimal, you may feel uncomfortable while using the VR headset for a long time. Some common symptoms are headaches, eye fatigue, dizziness, or neck fatigue.

WILL I RECEIVE ANY COMPENSATION FOR TAKING PART IN THIS STUDY?

Apart from my gratitude, you will not be compensated for participating in this research.

WHO WILL SEE THE INFORMATION THAT I GIVE?

All information gathered in this study will be kept as confidential as possible. Your privacy is very important to us, and the researchers will take every measure to protect it. Your information may be given out if required by law; however, the researchers will do their best to ensure that any released information will not identify you. No reference will be made in written or oral materials that could link you to this study. For this study, we will assign a code to your data so that the only place your name will appear in our records is on the consent form and our data spreadsheet, which links you to your code. Only research team members will have access to the link between you, your code, and your data.

The research team works to ensure confidentiality to the degree permitted by technology. It is possible, although unlikely, that unauthorized individuals could gain access to your responses because you are responding online. However, your participation in this online survey involves risks similar to a person's everyday internet use.

WILL MY DATA BE USED FOR FUTURE RESEARCH?

If you choose to participate in this study, your private information collected for this study will not be used or distributed for future studies, even if we remove all identifiers linked to you.

DO I HAVE TO TAKE PART IN THE STUDY (OR CAN I END MY PARTICIPATION EARLY)?

Your participation in this study is voluntary. You may refuse to participate in this study or any part of this study. You may withdraw at any time without prejudice. You are encouraged to ask questions about this study at the beginning or any time during the research study.

WHO TO CONTACT

For questions or concerns about the study, contact Ronaldo Canizales at +1 (970) 690-2319 [USA]. For questions regarding the rights of research subjects or any complaints or comments regarding the manner in which the study is being conducted, contact Professor Francisco Ortega, lecturer of the CS567 3D User Interfaces course, at f.ortega@colostate.edu.

PARTICIPANT CONSENT:

Your signature acknowledges that you have read the information stated and voluntarily wish to participate in this research. Your signature also acknowledges that you have received, on the date signed, a copy of this informed consent document containing ____ pages.

____   _______________________

Signature of participant   Date

____

Name of participant

____   _______________________

Signature of the person obtaining informed consent   Date

____

Name of person obtaining informed consent