The Future of Engineering Education
2024 Annual Conference & Exposition
Oregon Convention Center
Portland, OR . June 23 - 26, 2024
Paper ID #44266

Optimizing Virtual Learning: Advanced Recommendations for an AI Teaching Assistant

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Abstract

Virtual reality (VR) has emerged as a promising tool for training in many different areas, including but not limited to educating students on complex skills, providing a safe and immersive environment for practice, and learning from mistakes. However, VR-based training can be challenging, requiring students to learn to navigate the virtual environment and interact with objects differently than in the real world. This study exposed nine industrial engineering students in a virtual 3D printing environment to complete twenty different tasks to print a 3D object. The researchers observed students' gaze position, directions, and performance metrics, such as task completion time and accuracy, and their video recordings to provide recommendations for an AI teaching assistant that will provide automated feedback and assistance within the virtual learning platform. Based on the time lost in random searching, five tasks were identified that required further assistance in terms of AI teaching assistance. Video recordings also explored specific tasks that were difficult for new VR users to perform. The purpose of this study is to identify areas for improvement in the VR learning platform design with an AI assistant. This will allow users to learn course materials actively and effectively without supervision.

Keywords
Virtual reality (VR), AI teaching assistant, gaze behavior, performance measures, 3D printing

Introduction

Technological advances have shifted the popularity of 3D printing across industries, from automotive and aerospace to healthcare and construction. This versatile technology can create objects from various materials and is valuable for prototyping and manufacturing. However, learning 3D printing in real-life settings consumes resources and poses risks like machine failure and operator injury. To develop a safer training platform and conserve resources, the Human Factors (HF) and Sustainable and Intelligent Manufacturing (SIGMA) labs of the Department of Industrial, Manufacturing, and Systems Engineering at The University of Texas at Arlington created a virtual 3D printer lab. This virtual lab, similar to the physical SIGMA lab, aims to train students with cutting-edge technologies and manufacturing processes. This course project focuses on optimizing users' workforce training experience, one key component of human factors engineering research in Industrial Engineering (IE). Including cutting-edge technology like additive manufacturing allows IE students to explore improved and advanced opportunities for efficient and productive manufacturing.

Virtual Reality (VR) is a technological innovation that immerses individuals into a virtual environment (VE), creating a sensation of presence despite their physical absence [1, 2]. Over the past few decades, fully immersive virtual reality (VR) has gained popularity as a method of training and collaboration. In recent years, the educational landscape has witnessed a significant shift due to the emergence of VR as an unparalleled tool for immersive and interactive learning experiences. VR offers a unique environment where participants can engage in lifelike scenarios without requiring substantial physical resources and causing physical risks [3]. For example, Li et al. [4] studied construction safety training, and Wang et al. [5] studied natural disaster escape training using VR without exposing people to real threats. Researchers have also found that VR-based education has enduring learning outcomes for trainees due to its visually immersive experiences and interactive capabilities [6-7].

While VR is transformative, optimizing it for effective learning requires understanding user interactions. A virtual teaching assistant can enhance interactions, increase learning efficacy, and serve as a continuous improvement tool for student training. Different endeavors to improve VR training have been found in the education literature. Callaghan et al. [8] conducted a study where they explored integrating virtual reality, IoT, and voice-driven virtual assistants into remote laboratories for visualizing electrical phenomena, guiding students through experiments, and providing teaching resources. The researchers delved into the viability and long-term prospects of utilizing virtual reality and virtual assistants within this framework. In another study, Chheang et al. [9] introduced generative artificial intelligence (AI) and verbal communication to aid students in answering anatomy questions. Results show that generative AI with a vast database of information can provide comprehensive solutions to the students' customized needs. However, the researchers have yet to evaluate the quality and accuracy of AI's responses to future investigations. Muzurura et al. [10] leveraged AI-based voice-driven virtual assistants to enhance the learning environment in Zimbabwean higher and tertiary education. Most (around 84%) students were satisfied with the chatbot's performance and would use its service again. There are many examples of similar research [11, 12], and all of them have collected students' frequently asked questions-related data and instructors' provided answers. All these studies used natural language processing or large language models to create the AI models, which generated voice-based chatbots to provide students with information on their customized needs. The researchers performed user studies based on usability, trust, and satisfaction surveys. They stated that AI-based virtual assistants enhanced students' learning experiences and reduced the cognitive workload for both students and instructors. However, the accuracy of these systems still needs to be investigated and improved for most of these studies. Therefore, the AI design must explore factors like gaze behavior, performance measures, and user statuses (physical, mental, or emotional).

Analyzing users' gaze behavior, in this context, the way participants visually navigate and interact with the VR environment, is a novel way to evaluate and improve VR-based learning, aiding in developing an AI feedback system. This study explores these metrics for designing an AI teaching assistant for a virtual 3D printing lab. In this pilot study, part of a course project, students completed five types of interactions for twenty tasks to print a virtual 3D object, relying on clear symbolic and written instructions within VR. Gaze data provides insights into where and how long participants look inside the VR, offering a good understanding of their behavior in various situations. Therefore, an AI assistant based on gaze behavior will provide a comprehensive understanding of the learners' actions, helping enhance the learning experience.

This research answers the following two questions to improve student learning: (1) Which interactions or tasks within the virtual lab consume the most time? (2) What segments pose significant challenges for participants to navigate or comprehend? This study uses information from how people look around in VR to create assistive instructions with AI. These instructions will help with steps that are hard to find in VR or activities that are difficult to complete in VR. This sophisticated analysis and AI mix is a big step for 3D printing lessons in VR.

The paper explores an innovative educational component integrated into a course project at the authors' university. They focused on teaching students about 3D printing process parameters and safety. In addition to traditional teaching methods, the curriculum incorporates immersive experiences in virtual reality (VR) and introduces students to advanced techniques in gaze data analysis. This approach not only enriches students' understanding of contemporary technologies but also equips them with valuable skills in data analysis, aligning with the demands of modern industries. By blending theoretical concepts with hands-on experiences in cutting-edge technologies, the educational component fosters a holistic learning environment, preparing students for the dynamic landscape of additive manufacturing and data-driven decision-making.

Materials and Methods

A virtual learning environment was created using the Unity game engine, and students were immersed in it using the HTC Vive Pro Eye headset. The virtual environment included two different scenarios. The first scenario exposed students to a VR familiarization room (See Figure 1), where they learned how to navigate by teleporting, interact with each object using controllers, and read instructions to complete assigned tasks.

Figure 1. Virtual familiarization room

Once they had completed all the assigned tasks in the familiarization room, they entered the second scenario, which presented the 3D printer lab. In the printing room, there were four stations and twenty assigned tasks. The four stations included (i) a preparation station, (ii) a control station, (iii) a printing station, and (iv) a post-processing station (see Figure 2). The twenty tasks have been divided into five categories based on interaction type, such as (i) teleportation without carrying objects, (ii) teleportation with carrying objects, (iii) grabbing objects, (iv) moving objects, and (v) selection of choices.

Figure 2. Virtual 3D printing lab

Categorizing the tasks helped to identify similarities among them. It allowed for analyzing properties such as value-added time, non-value-added-time, and error-based actions on the type of interactions. Figure 3 presents a list of twenty tasks categorized according to their kind of interactions. The number preceding each task description indicates its sequence in the series. Different types of instructions were utilized to help students with the tasks in the VR, such as symbols (arrows, markers, etc. within VR) and written hints. Figure 3 shows the grouping of twenty tasks into five interaction types.

A total of nine students (six males and three females, age range 22-35 years) participated in the study. None of these nine students had any experience using VR; however, six were familiar with 3D printing. The students were initially screened through a simulation sickness questionnaire (SSQ) [13] regarding simulation sickness, which can occur from exposure to VR. A survey was developed using Jotform to evaluate students’ mental workload, difficulty, and satisfaction while using the learning platform.

Teleportation without Carrying Objects	1: Teleport to the preparation station 9: Teleport to the control station and follow instructions on the computer screen 13: Teleport back to the preparation station 16: Teleport back to the control station and click the "Start Printing" button
Teleportation with Carrying Objects	6: Grab the build platform and teleport to the printing station 14: Grab the desired powder box and teleport to the printing station 18: Grab the build platform and teleport to the post-processing station
Grabbing Objects	2: Grab and wear the lab coat 3: Grab and wear the face mask 4: Grab and wear gloves 5: Grab and wear the goggles
Moving Objects	7: Open printer door 8: Crouch down and insert the build platform into the printer 15: Insert the powder into the printer 17: After printing, let build platform cool down and remove it from printer 19: Insert the build platform into the post-processing station
Selection of Choices	10: Choose the right material on the computer screen 11: Choose the correct layer thickness on the computer screen 12: Choose the proper orientation on the computer screen 20: Follow the instructions on the screen to complete the post-processing

Figure 3. Task category based on interaction type

Once each student arrived in the Human Factors lab, they were given a consent form, demographic survey, SSQ, and a short brief about the purpose of the study. Then, they were first exposed to the familiarization room and the virtual 3D printing lab. In the printing room, students started by wearing personal protective equipment (PPE) at the preparation station. Then they grabbed the build platform and teleported to the printing station. They opened the printer door at this station and correctly put the build platform inside it. After this, they went to the control station and selected material, layer thickness, and orientation from the screen. Once they selected the operational parameters, they returned to the preparation station to grab the chosen powder material and teleported to the printer station. They opened the printer's top door to insert powder material at the top-right side. Following this, they returned to the control station and pressed the ‘Start Printing’ button on the screen. Once the printing was completed, students took the build material from the printer and teleported it to the post-processing station. They inserted the build material into the post-processing station. This procedure mimics a real-life 3D printing process using a Selective Laser Sintering (SLS) printer.

During the study, the students did not need assistance to complete the task. The entire session was video recorded. Cognitive3D, a data analytics platform, was used to collect students' gaze behavior and interaction data for each task that they completed. These data include gaze direction, time and frequency for focus, task completion time, and accuracy in completing each task. After completion of the study, students were given the post-study survey asking about their mental workload and experience. This study was part of a course project for students, and no compensation for participation was provided. The methodology of the study is summarized as shown in Figure 4.

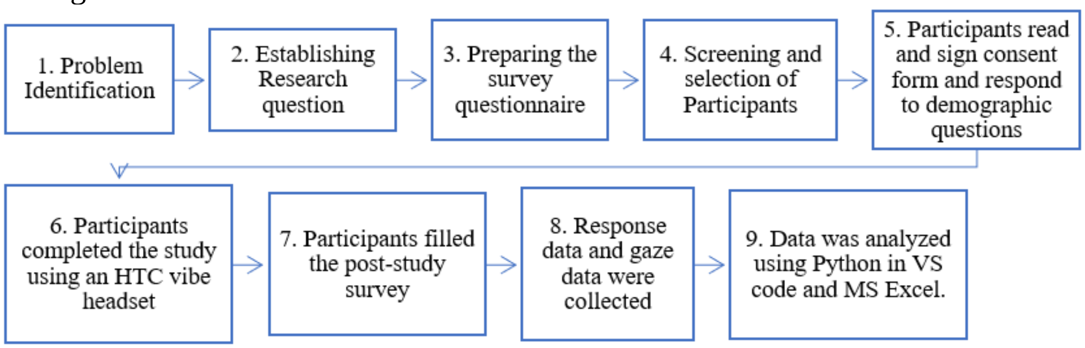

Figure 4. Methodology of the study

Results

Data were obtained in two ways: one from the self-reported survey and another from the cognitive3D analytics platform in .csv format for student interactions and .json file format for gaze location and directions. The survey contained fifteen questions designed to obtain user comfort level and the areas where they found it challenging to complete the tasks.

Upon analyzing the survey data, several vital observations have emerged. Some participants reported challenges regarding visibility and ease of utilizing the teleportation function within the VR environment. Despite these hurdles, the overall sentiment towards VR usability remained positive, with most participants finding it enjoyable and easy to use.

Further analysis revealed specific task-related difficulties within the VR environment. Participants found grabbing objects, selecting parameters, moving the printer door, and navigating to the post-processing station particularly challenging. While satisfied with the existing instructions, they preferred hint-based written guidance over verbal or visual cues. Notably, most participants found the 3D printing process easy to perform. These findings highlight the need to refine certain aspects of VR interactions. Optimizing teleportation mechanisms and providing more intuitive task-specific guidance, mainly through written hints, could significantly enhance the user experience for VR-based training on 3D printing.

Regarding the completion time for all twenty tasks, the mean is 21.77 minutes, with a minimum completion time of 14 minutes and a maximum completion time of 35 minutes. Table 1 shows the mean completion time for each task in seconds. It was found that students spent the most non-value-added time completing task 6: Grab the build platform and teleport to the printing station. The following five tasks, as highlighted (bolded and italic) in Table 1, based on the most unused time, include Task 7: Opening the printer door, Task 15: Insert the powder into the printer, Task 18: teleporting to the post-processing station, and Task 19: Inserting the build platform into the post-processing station.

Table 1: Tasks with value-added and non-value-added times (in seconds)

Task Category	Sequence and Name of the Task	Value-added time	Non-value-added time	Total
Teleportation w/o Objects	1: Teleport to the preparation station	27.52	1.78	29.30
	9: Teleport to the control station to follow instructions	76.04	8.93	84.98
	13: Teleport back to the preparation station	48.12	5.25	53.35
	16: Teleport to control station to start printing	26.89	8.89	35.80
Teleportation with Objects	***6: Grab build platform and teleport to printing station***	61.04	***50.82***	112.00
	14: Grab selected powder box and teleport to printer	16.21	8.80	25.00
	18: Take build platform to the post-processing station	30.90	***19.08***	49.90
Grabbing Objects	2: Grab and wear the lab coat	17.43	3.30	20.73
	3: Grab and wear the face mask	49.98	2.58	52.50
	4: Grab and wear gloves	79.00	14.99	93.98
	5: Grab and wear the goggles	68.62	19.36	87.97
Moving Objects	***7: Open the door of the printer***	37.78	***49.74***	87.56
	8: Crouch down and insert the build platform	22.93	16.55	39.50
	15: Insert the powder into the printer	60.45	**35.55**	96.10
	17: After printing, remove cooled build platform	36.04	14.59	50.60
	19: Insert build platform into post-processing station	18.64	***24.07***	42.70
Selection of Choices	10: Choose the right material on the computer screen	26.27	0.04	26.30
	11: Choose the correct layer thickness on the computer	113.47	3.35	117.00
	12: Choose the proper orientation on the computer	56.03	0.85	56.90
	20: Follow instructions on the screen for post-processing	8.44	4.28	12.70

The researchers have also analyzed gaze data in X and Z directions to draw heat maps. A heatmap visualizes the regions on a screen where a person's gaze was most frequent or lingered the longest. In Figure 5, brighter yellow hues highlight the heightened focus from participants, indicating value-added time spent, whereas blurred areas denote regions receiving less attention and random wandering, indicating non-value-added time spent. Notably, the task 'teleport with carrying' exhibits the most scattered heat map; tasks 6 and 18 fall into this category. This implies that participants frequently needed to look around because they were unsure what to do. This result aligns with the findings based on value-added and non-value-added time presented in Table 1. The 'moving objects' category also shows a scattered heat map, encompassing tasks 7, 8, 15, 17, and 19. Among these tasks, 7, 15, and 19 exhibit the highest non-value-added time in Table 1. The non-value-added time and gaze heat map findings highlight areas for improvement, particularly in tasks where incorporating an AI assistant could enhance students’ learning experience.

In addition to the gaze data and survey data analysis, the researchers observed the participants' video-recorded activities while completing the study. From the observation and the video data analysis, the following tasks were found to be difficult for the students: Task 6 - teleporting after grabbing the build material, Task 19 - inserting the build material into the printer, and Task 15 - inserting the powder into the printer. For the basic interactions with the help tablet for instruction materials and for navigation in VR, participants were struggling with operating the help tablet and teleporting instead of walking to a specific station.

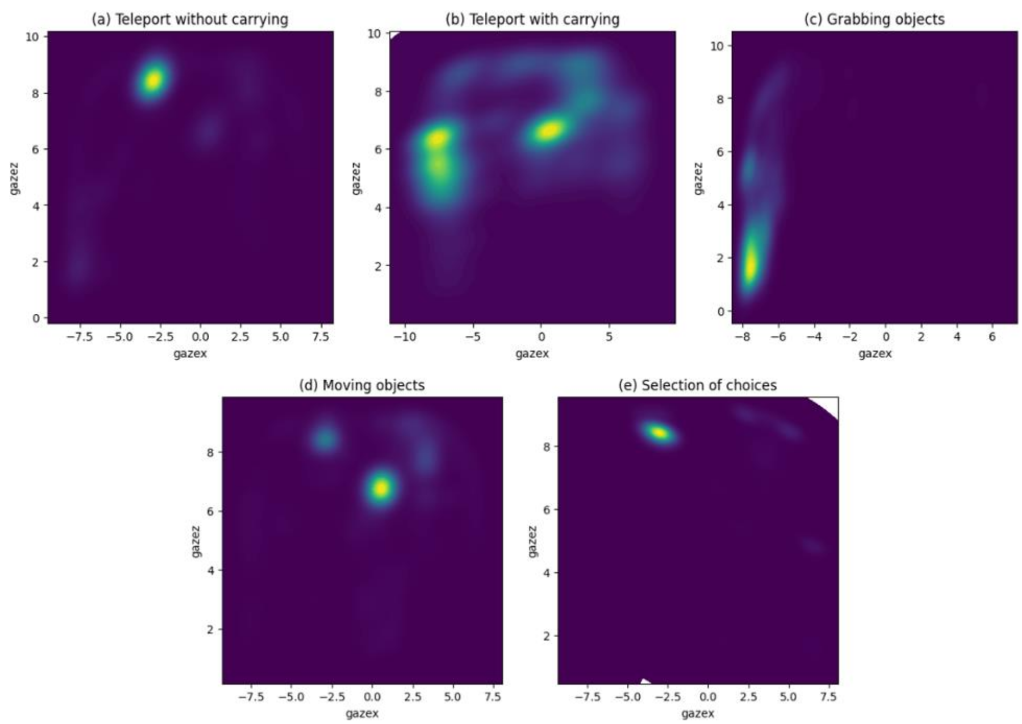

Figure 5. Gaze heat map data of task category (a) teleport without carrying (b) teleport with carrying (c) grabbing objects (d) moving objects (e) selection of choices

Discussions

Analyzing several data sets, including surveys, user gaze behavior, and video recordings, obtained a comprehensive understanding of the user experience in virtual reality. A Pareto analysis shown in Figure 6 presents interactions with the most crucial problems based on their time spent on non-value-added activities. Several tasks were identified as the ones where individuals faced the most difficulties. These places require modification through artificial intelligence to improve the efficacy of 3D printing training in virtual reality. As each participant was facing different problems, user action-based AI assistants will be more useful than knowledge-based AI. Most past research has created knowledge-based AIs that can only provide information on users’ requests [8-10].

Certain activities, such as moving objects and placing them in the correct position and in perfect orientation, were difficult for students. There are different types of movements, such as longitudinal, lateral, or rotational. Due to their complexity, making objects move in different directions and varied ways is often simplified in VR. Because, aligning human movement in a virtual world with virtual objects is challenging [14]. Simulating the physics of objects can also be computationally intensive.

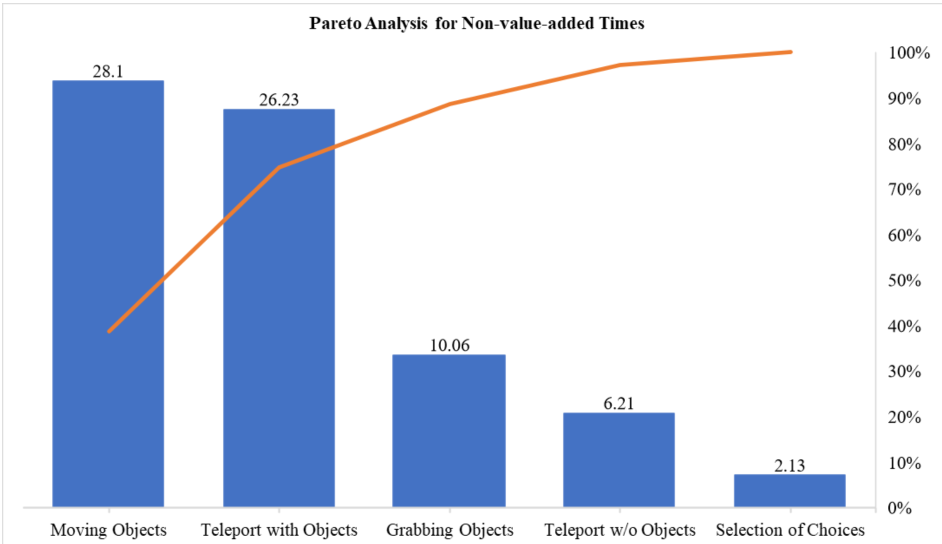

Figure 6. Pareto analysis to identify vital problems

Another area for improvement is teleporting while carrying objects. The absence of optical flow can impede participants' ability to estimate distances traveled accurately [15]. The use of one controller to teleport to the right position while also needing to use another controller to hold the object to be carried made it challenging. Moreover, teleportation has been criticized for disrupting the feelings of presence and realism [15], as it enables users to engage in actions that defy real-life constraints. AI assistants can detect the wandering gaze movement of participants during teleportation. This detection can help generate written hints for using both controllers successfully so that students can carry the object to the new position. Proper directional cues, like arrows and augmented colored paths, can also help students find the right position to teleport. Both these tasks could benefit from additional assistance, such as AI-driven hints or instructions, to improve efficiency and reduce completion time, as well as reduce non-value-added time. With assistance from AI, the non-value-added times can be significantly improved to make the training more effective and efficient.

The study indicates that instructions lacking salient features can impact users' performance. Most participants felt at ease using VR, while merely one participant mentioned having issues like eye strain or headaches. The fact that discomfort was absent throughout the VR experiment implies that it was well-received. Since participants had little to no experience with VR beforehand, it suggests that the study findings can apply to people who are new to VR technology.

Based on our observations and results, we propose several recommendations guided by established user interface design principles [16]. To improve spatial awareness and navigation, we recommend implementing a full-room view feature, aligning with Nielsen's system status visibility principle [17]. Additionally, incorporating distinct visual cues for objects like the powder box and printer can enhance object identification and simplify task completion. Furthermore, displaying contextual instructions or directional arrows after grabbing specific objects aligns with the design principle of mapping, ensuring precise and predictable relationships between controls and actions.

To enhance feedback and user interaction, we recommend implementing informative feedback mechanisms like audible or haptic cues after completing tasks, aligning with the principle of the match between the system and the real world. Additionally, clearly labeling objects and stations within the VR, following the principle of consistency and standards, can reduce confusion and ensure consistency with the real-world setup. The proposed recommendations and associated design principles can pave the way for a more user-friendly and intuitive VR-enabled 3D printing experience by continuously conducting user testing and integrating valuable feedback.

The study involved several limitations. First, the number of participants was deficient and lacked equal representation of age and gender distributions. Since none of the participants had previous experience with VR, the effect of variability in familiarity with VR could not be captured. Also, few participants may have shown a bias toward positive reviews while completing the survey questions. As this study was part of a course project and only students enrolled in the course were able to participate, there was not much flexibility to eliminate these population-based limitations. However, future research with a larger scope should focus on addressing them.

Conclusions

Our study explored how people experience 3D printing in virtual reality (VR). We identified the challenges users face by analyzing surveys, observing user behavior, and studying user interactions. These difficulties point to the need for AI implementation in VR tasks. Simplifying processes, like navigation and task completion, could significantly boost user satisfaction and efficiency. Despite minor issues, the positive response from participants, especially VR newcomers, suggests broad applicability. Our practical recommendations, rooted in design principles, aim to enhance spatial awareness, object recognition, and user feedback. Recognizing limitations, like a small participant pool, emphasizes the importance of ongoing testing and feedback for refining the VR 3D printing experience. Our findings provide practical insights for creating a more user-friendly and intuitive VR-enabled 3D printing environment.

Acknowledgment

This material is based upon work supported by the National Science Foundation under Grant No. 2202598.

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