Use of Eye Behavior With Visual Distraction for Attention Training in VR

Yi (Joy) Li* Kennesaw State University
Pranathi Ayyalaraju Ramalakshmi † Kennesaw State University
Chao Mei ‡ Reality Labs, Meta
Sungchul Jung § Kennesaw State University

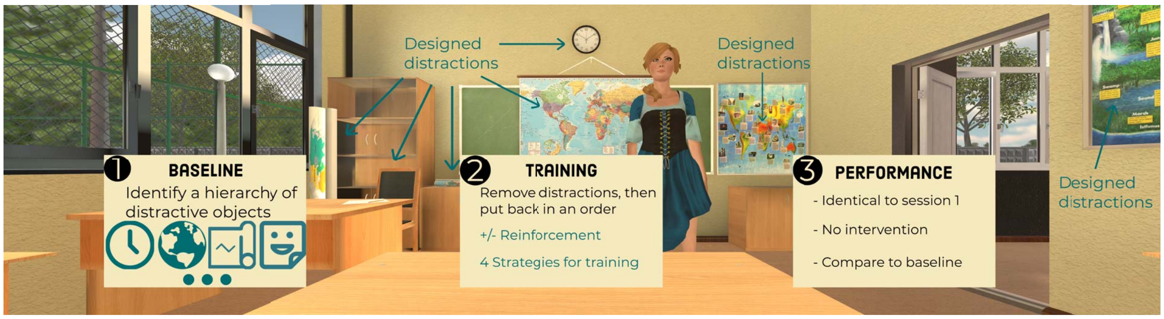


Figure 1: Flowchart of the proposed VR system

Abstract

Concentration and attention skills are critical to human beings in almost every area of society, including school, work, and relationships. Especially, improving and increasing attention skills for certain people with social impairments such as Autism Spectrum Disorders, will assist their intervention and benefit their life quality. Virtual reality (VR) with a behavioral analysis system can help attention training with more customized scenarios for interaction and a fully controllable virtual environment that is often not available in real life. In the current phase, a system prototype was developed and a preliminary study with young adult participants was conducted to collect the baseline and validate the design. A within-subject design was used to embed four different training strategies in the training session. A total of 20 participants were involved in the preliminary experiment. The results of the data analysis show that even though eye gazing on certain objects decreased as expected, the total distraction time was rather on the opposite trend. The results have brought up new insights into the study and will inspire more improvement in future steps.

Keywords: virtual reality, embodiment, human-computer interaction, autism, attention training

Index Terms: Human-centered computing [Human computer interaction (HCI)]: Interaction paradigms—Virtual reality; Human-centered computing [Interaction design]: Interaction design process and methods—Scenario-based design

1 Introduction

It is well known that tracking eye gazing information in VR intervention training provides valuable information on the trainee's status, such as the trainee's attention information [1]. With the eye-tracking embedded head-mounted devices (HMD) we expanded the attention training to the special group who have impairment in attention skills, such as children with Autism Spectrum Disorder (ASD). ASD is a spectrum-based disorder that occurs in early childhood due to neurological disorders, and its symptoms include abnormal social skills, communication skills, interests, and behavior patterns [2]. The development of technical tools to help and train children with ASD has been identified as a priority research domain [3] since traditional medicine or healthcare approaches are limited to curing ASD. To address the problem, we propose an adaptive virtual environments therapy system (AVET) that uses the exclusive feature of VR "impossible experiences" that is not explored in other simulations or real-world interventions for ASD. We consolidated the theoretical foundation [4, 5] and improved the AVET system based on Zhang et al's work [6]. In this paper, we aim to: (1) Introduce the developed AVET system prototype - VR attention training therapy using eye gazing methodology with a virtual objects hierarchy for attention determination and training, (2) report the current phase of data collection through a preliminary study that will lead to the next phase of empirical study. (3) analyze the data to ensure appropriate identifying eye gazing attention from eye-tracking data. In the current study, a preliminary user study with 20 participants has been conducted to test the effectiveness of the methodology of eye gazing attention determination.

*e-mail: joy.li@kennesaw.edu
†e-mail: payyalar@students.kennesaw.edu
‡e-mail: meichaomc@gmail.com
§e-mail: sjung11@kennesw.edu

2 Related Work

Although considered a childhood condition, ASD impairments are generally life-long, and 1 in 44 children have autism in the US [7]. People with ASD typically suffer from deficits in communication, emotional capacity, social interactions, and repetitive behavior patterns that affect their ability to develop their driving skills because of problems with changing their focus, doing consecutive tasks, integrating their cognitive and motor processes, and coordinating their movements. [8]. In attempting to leverage advanced technologies in tools that assist healthcare, the number of studies boosted in exploring using VR for intervention and training. As of June 2022, we gathered 44 articles and five review papers published between 2010-2022 related to using VR for educational purposes for ASD [5]. The research focus of the studies is summarized in Figure 2.

Bozgeyikli et al. [9] summarized studies using VR (immersive and non-immersive) prior to 2018 that targeted ASD teaching or educational training. The research targets three types of skills: social, life and safety skills. The mainstream use of immersive VR on the market nowadays includes HMD and CAVE. Ten studies using

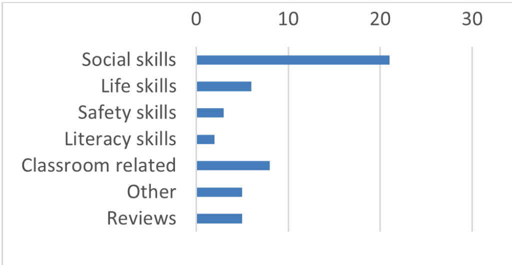


Figure 2: Number of articles by research focus.

immersive VR, with three to four under each skill category, yielded positive training results and successful transfer of learned skills to real life. Design principles were proven effective for autism and aligned with these for typical inclusive education, such as embodied learning, feeling of control, goal orientation, repetition, task complexity, and rewards with feedback. One common limitation of the discussed studies is insufficient fidelity due to the small average number of participants (only 7).

Dechsling et al. [10] reviewed VR and AR studies specifically to improve the social skills of people with ASD. Forty-nine studies were identified. Aligning with our research goal is that social skills are the most targeted in using VR to help autism. These studies show that young children, adults, and female participants are less targeted. Rigorous research designs and evidence-based study strategies are needed.

Several studies have been conducted using a VR driving simulation for autism training and assessing the use of eye tracking [11,12]. The studies indicated that rich information from eye gazing data, such as blink rate and pupil diameter, can be used to infer a user's mental cognitive state, and thus be used in training to improve attention skills.

In the proposed study, we designed and developed a new attention training system using VR as a tool and integrated it with four different strategies. To the best of our knowledge, no other studies have customized the VR scenarios to integrate with tracking and dynamic adaptation in training, creatively applied four different feedback types in learning theories into training strategies, and also fully made use of visual or sound cues in rewards and punishment.

3 Methods

The system is designed to be hosted by a graphics card of at least 1080Ti and an HTC VIVE Pro Eye headset. In this study, participants were asked to wear the HMD with sitting on a chair and resting their arms on the chair seat (See Fig 4). We used Unity Game Engine 2021.3.2f1. for development and logged the captured data.

3.1 Instruments

3.1.1 Eye-tracking Data

The HMD is equipped with eye tracking capability accurate to 0.5° - 1.1° and a trackable field of view for 110°. Gaze origin, gaze direction, pupil diameter, pupil position, eye openness, and the total length of time that users spend looking at any object in the scenes are gathered and then analyzed.

3.1.2 Physiology Data

Empatica E4 wristband [13] is used to monitor and record physiological signals. It is a medical-grade wearable device that streams real-time physiological signals and records the data. Sensors are embedded inside the wristband to monitor interbeat intervals (IBIs), heart rate variability (HRV), and electro-dermal activity (EDA), as well as several other acceleration and temperature measures. Our main interest focuses on arousal parameters, including heart rate (HR) and galvanic skin response (GSR). They are stored for later phases with the plan to compare them through different group conditions in pairs with autistic participants. We recorded the physiological signal in real-time during the experiment sessions using a mobile device and stored the data once each participant completed the sessions.

3.2 Scenario Design

The system consists of three sessions of virtual lectures with four different training strategies. In each lecture session, the user is placed in the same location of the same virtual classroom, and tasked to pay attention to a virtual teacher as she gives a lecture for around five minutes. The contents of the lectures are randomly selected from TED Talks. They are presented in a counter-balanced design to ensure that the user is not presented with the same lecture twice and also trimmed at a natural stop of TED speeches (i.e. the end of the explanation of some concept or a statement). The five minutes length per clip for a total of three clips was chosen because the participants are teenagers or young adults, and the recommended total time for a one-time VR experience is under 30 minutes. The teaser picture Figure 1 depicts the flow of the three different sessions and the design of the virtual classroom.

First Session This is the baseline session for the system to observe and collect useful data. While the user is listening to the lecture given by the teacher, the system tracks their eye gaze to identify a list of potential distractions in the current environment. Distracting objects associated with the longest continuous gazing time on them are recorded.

Second Session This is the training session. Four strategies using either positive reinforcement or negative reinforcement are designed to be used in the session. At the beginning of the lecture in the second session, the system first removes all objects that were marked as distractions during the first section. These distractions are then added back into the scene one after another in a particular order, in order to let the user adapt to the training. Throughout this session, the system applies one of four training strategies to direct the user's attention back to the virtual teacher when the system detects that they are distracted.

Third Session This is the performance session. It has identical settings as the first session except for different lecture content. The system gathers the user' gazing pattern data while the virtual teacher is lecturing, with no training strategies or guidance. This data will be compared to the first session to assess the effectiveness of the training session (second session). The methodology of eye-gazing attention determination and training strategies are described in the rest of this section.

In between each session, the participant will be advised to take a break. The GSR and HR readings of the wristband will serve as indicators to make sure that the participant has reset the biometric level before continuing to the next session.

3.3 Training Strategies

As mentioned in the Scenario Design section, the second session is the training session with four different training strategies. Operant conditioning is used as the base theory, upon which negative and positive reinforcement and punishment are designed as strategies to help users adapt to the distractions and keep focusing on the teacher. The four training strategies are described in the following paragraphs.

Positive Reinforcement [14]: Anticipated behavior is rewarded by positive reinforcement through a scoring system that rewards the users' behavior. There is a score UI, where the score goes up when the user pays attention to the virtual teacher. Combining token economy theory, after the training session, the user can spend their score to buy trinkets. More specifically, ray-casting from VIVE HMD's eye tracking is implemented to determine what the user is looking at. The rays are constantly checked to see if they hit the virtual teacher. While the rays hit the teacher, the score goes up at a steady speed. When the rays do not hit the teacher, the score remains the same. There is no deduction or punishment on the score if the user looks away.

Negative Reinforcement [15]: Negative reinforcement means a subject will try to avoid something bad happening by doing the correct activities. In the second strategy, negative reinforcement is designed by overlaying a red vignette on the user's field of view to resemble an effect many video games use to indicate damage. Same as in other strategies, eye tracking projects rays that follow the user's gaze and check whether the rays hit the teacher or not. If they do hit the teacher, the system will decrease the opacity of the vignette at a preset speed until it disappears entirely. Otherwise, if the rays do not hit the teacher, the system will increase the opacity of the vignette at the same speed until it becomes fully visible. The user will be very likely to avoid such uncomfortable visual effects by switching attention from the distraction objects to the target objects.

Positive Punishment [16]: In the third strategy, we include positive punishment to discourage undesirable behavior by adding an unwelcome stimulus. A 10 kHz tone is applied to dissuade the user from looking at the distraction. Moreover, the volume of the noise has a direct proportion to how long they have been distracted by the object. Again, the system checks the user's eye gazing rays to see if it hits a distracting object. If they do, the system raises the volume of a mosquito sound at a set speed until it hits full volume. In contrast, when the user's eye-gazing rays hit the teacher, the volume of the noise goes down.

Negative Punishment [17]: Negative punishment means taking away something the user values to discourage undesired behavior. In the fourth strategy, negative punishment is implemented by reducing the opacity of the distraction object. If the user's gaze hits a distracting object, the opacity of the distraction object is reduced at a set speed until it becomes fully transparent. In addition, at the beginning of the user study, we will adjust the maximum audio volume and the opacity of the red vignette to make each user feel comfortable during the study.

3.4 Gaze Determination Methodology

An eye gazing attention determination algorithm is designed to distinguish whether a virtual object is distracting the users' attention from what they are tasked to do in a virtual environment. The proposed system keeps three timers for each object. The Total Gaze Time (TGT) documents the total amount of time the user focuses on gazing at that object during the current session. The Continuous Gaze Time (CGT) records the amount of time the user has spent continuously looking at the object without glancing away. The Cool Down Time (CDT) keeps track of how much time has passed since the user last looked at the object. The CGT and CDT for each object are compared to set threshold values to determine whether the object is significantly distracting to the user. The detailed relation between these values and the state transitions is shown in Figure 3 as two Finite State Machine diagrams and explained as follows.

When the system detects that the user is focusing on a virtual object that has not been marked as distracting, the object's TGT and CGT are increased. When the object's CGT reaches a certain threshold, the system marks that object as a distracting object and adds it to the list of distractions. The current system uses a CGT threshold value of 3 seconds. The length of the CGT threshold is based on previous research [4]. On the other hand, when the system perceives that the user is no longer looking at an object, that object's CDT rises. When the CDT hits the CDT threshold, the object's CGT is reset to zero. The current system has a CDT threshold value set to 1 second. When an object has been marked as a distraction, it no longer tracks its CGT. However, when the system identifies that the user is focusing on a distraction, that object's TGT keeps going up. The TGT for each object is tracked throughout the entire session and is recorded alongside the user's eye metrics including gaze origin, gaze direction, pupil diameter, pupil position, and eye openness. In order to maintain the user's immersion and user experience, a hierarchical structure is introduced to the potentially distracting objects in the scene. The hierarchy is used to determine the order in which objects reappear in the scene during the training session to ensure that no object returns before the object holds it. For example, a desk holds a map, some papers, and a pen above the papers. Then the desk will always reappear earlier than the papers, and papers earlier than the pen. Items not in the same hierarchy reappear in random order since there is no conflict.

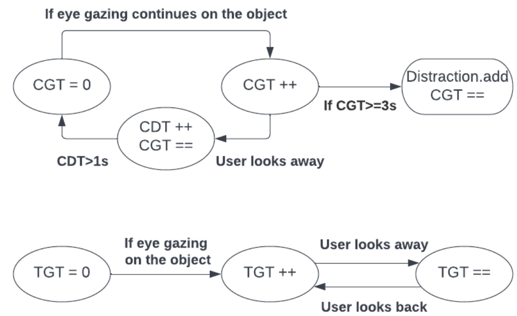


Figure 3: State transitions of three timers. "++" means an increase by time, "==" means pause, and "xx=0" means resetting the variable to zero

4 Preliminary Study

4.1 Participants

The VR experiment is advertised for recruiting students on both campuses at the university, as well as on the social media platforms of the university. Interested potential participants contact the researcher team and got a self-screening form. Questions about demographic data are collected including age, gender, and if they have a physical or mental health condition and familiarity with VR. In the current phase, we have recruited 20 participants in total with 6 females and 14 males.

4.2 Procedures

The experiment is designed in the following steps: Firstly, a researcher instructs and explains the consent form. A GoPro Max with 360° camera is used to record the entire experimental session. The E4 wristband is then attached to the participant's preferred side of the wrist. Afterward, the researcher helps the participant put on the headset. No controllers or gamepads are needed for participants to move virtually in this current study. All interactions are completed by head movement and eye gaze, therefore an eye-calibration and Interpupillary Distance (IPD) are adjusted. The participant then adjusts and starts the game. There are two monitors used during the game sessions. One screen is used to stream the VR scenes that the participant is experiencing, and the other is used to monitor the real-time wristband readings on GSR and heart rate. Figure 4 shows the setup for an experiment session.

Each session is set to be around five minutes of a lecture at a natural stop. After each session is done, the participant may take as much time as needed to relax and recover until he/she is ready for the next session. The participant will be assisted in taking off the headset if necessary. The GSR and HR readings of the wristband serve as

Figure 4: Participant setup

Open question
P1. Which three items do you remember the most in the VR classroom?
Reflection of design
P2. I like to take classes in such a virtual classroom
P3. Was the game easy to understand?
P4. I feel more concentrated than in the traditional classroom
P5. If you could change the game in any way, what would you change?
Single question
P6. How likely would you recommend this game to a friend?

Table 1: Post-session questionnaire.

indicators to make sure that the biometric level of the participant has reset before continuing to the next session.

After all three sessions are completed, the participant will be given the post-test questionnaire to complete. The average total time per participant is 25 minutes, including all consent, surveys, VR sessions and break time.

4.3 Data Collection

The data collected during the experiment is listed as follows:

1. Demographic information: Gender, age, vision, general physical and mental health condition, the possibility of motion sickness, and familiarity with VR games are collected through a pre-screening form when signing up participants.
2. In-game attention performance: Gaze direction, pupil diameter, and eye openness are gathered throughout all three sessions using the eye-tracking sensor on the headset. Gaze direction is used to identify distractive objects and calculate distraction time as mentioned in section 3.4. Pupil diameter and eye openness are collected to compare the difference in session 1 and session 3, to see if they are associated with attention.
3. Post-session questionnaire: the questions on the questionnaire are listed in Table 1. Yes/No/Maybe are used for most questions except open questions and P6, which uses a 5-point Likert Scale.

4.4 Results

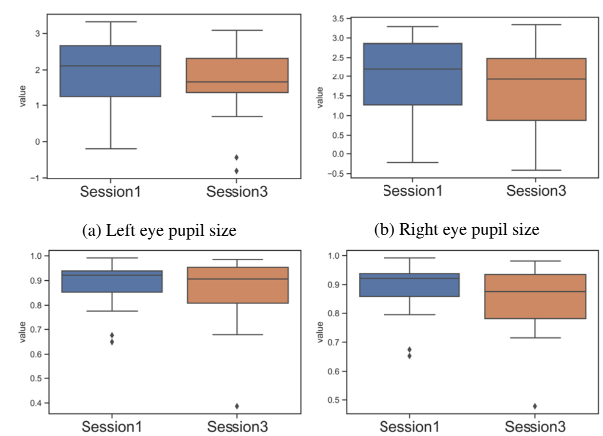
All statistical analysis on quantitative data was done using Python. Normality and equality of variances were performed. A significance threshold of 0.05 was used for all the tests.

Demographic information The demographic information of the participants is summarized in Table 2.

Variable	n	%	Variable	n	%
Gender			Age		
Female	6	30	under 18	0	0
Male	14	70	18 or over	20	100
VR experience?			Motion sickness?		
Yes	13	65	Yes	5	25
No	7	35	No	15	75
Physical illness?			Attention deficit condition?		
Yes	0	0	Yes	0	0
No	20	100	No	20	100

Table 2: Demographic information of participants

Eye Behaviors A paired t-test was performed to compare the eye behavior data between session 1 and session 3. The results reveal that there were no statistically significant differences in left eye pupil size ($t(19) = 1.118$, $p = 0.28$), right eye pupil size ($t(19) = 0.928$, $p < 0.36$), left eye openness ($t(19) = 0.827$, $p < 0.42$) and right eye openness ($t(19) = 1.354$, $p = 0.19$). Figure 5 shows the comparison.



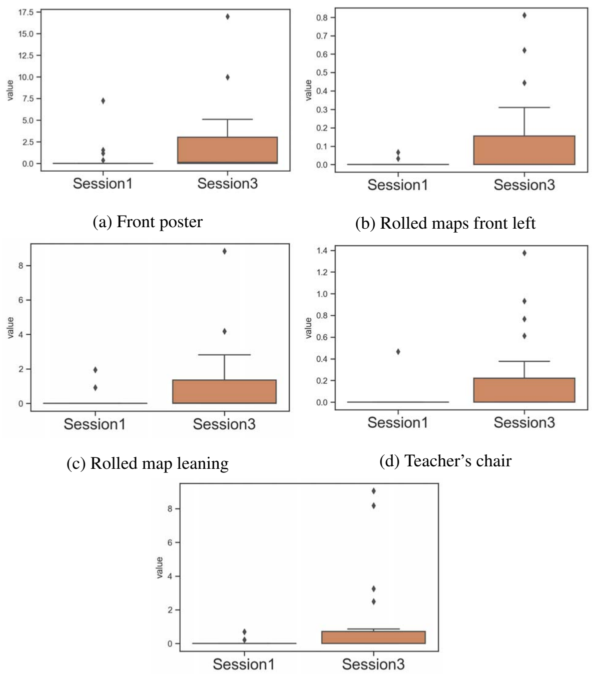
(a) Left eye pupil size (b) Right eye pupil size

(c) Left eye openness (d) Right eye openness

Figure 5: Eye behavior comparison session 1 vs. session 3

Distraction objects and time A paired t-test was performed to compare the nonzero distraction time between session 1 and session 3. The results reveal that there are statistically significant differences in several objects but not all. These are: the front poster ($t(19) = -2.670$, $p = 0.015$), the front left rolled maps($t(19) = -2.263$, $p = 0.003$), the leaning rolled map($t(19) = -2.125$, $p = 0.015$), the teacher's chair($t(19) = -2.458$, $p = 0.023$), and the short cabinet($t(19) = -2.584$, $p = 0.018$). Figure 6 shows the comparison of the five objects between session 1 and session 3. This observation is the opposite of our expectation, meaning these objects drew more attention after the attention training session.

All objects in the VR classroom are able to keep track of the distraction time, the total number of objects (timers) is 53. The top five objects that attracted the most time for all participants are the front world map, the blackboard, the front poster, the right poster 2, and the front left tall cabinet. Their average distraction time change between sessions 1 and 3 are plotted in Figure 7. Except for the



(a) Front poster

(b) Rolled maps front left

(c) Rolled map leaning

(d) Teacher's chair

(e) Short cabinet

Figure 6: Distraction time on objects session 1 vs. session 3

front poster, the other four objects received lower gazing time after the attention training session.

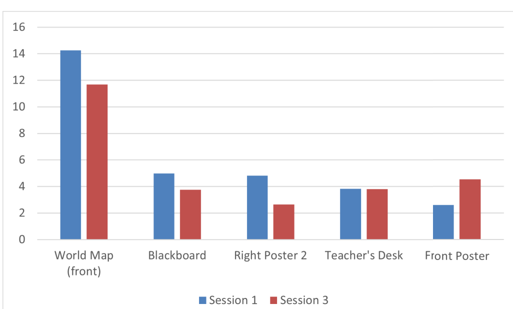


Figure 7: Top five distraction times and the session comparison

Four strategy comparison A one-way ANOVA was performed to compare the effect of the four different strategies used in training session 2. There was not a statistically significant difference between groups ($F(3,19) = 2.33$, $p = 0.11$). Figure 8 shows the box plot of the distraction difference by strategies.

Post-session Questionnaire For the post-session questionnaire, since it is optional, we have received 14 responses out of the 20 participants. 50% indicated they would not be opposed to taking classes in such a virtual classroom, and 100% completely understood the purpose of the application. 64.3% mentioned they did not feel more concentrated than in the traditional classroom, and 92.8% would like or at least would not be opposed to recommending the VR experience to their friends. The most impressive three virtual objects being voted are the teacher, the world map, and the clock, as shown in Figure 9.

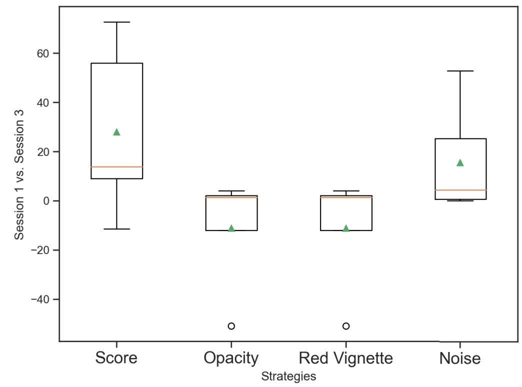


Figure 8: Distraction time difference by strategies

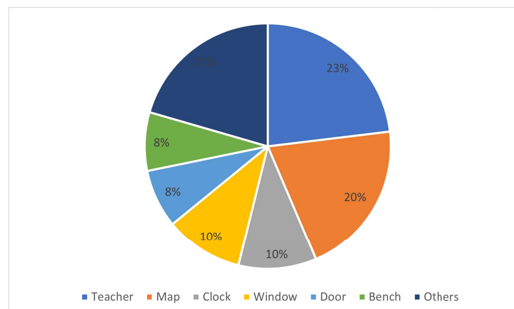


Figure 9: Most impressive objects in post questionnaire

5 Discussion

The data analysis results partially rejected our expectation that the designed training strategies with positive or negative reinforcement or punishment feedback reduce the distraction time and therefore increase attention skills. Even though eye gazing on certain objects decreased as expected (more particularly, the most obvious ones that attracted more time in the beginning), the total distraction time was rather the opposite: after the training session, more participants started to look around the virtual classroom.

As the results of the distraction data analysis are rather surprisingly the opposite trend from our expectation, a follow-up interview was arranged immediately to ask the question: Did you get distracted more in session 3 and why? The 19 pieces of feedback we collected are shown in a pie chart as Figure 10. More than half (58%) of participants indicated that they did not realize that they could see all the dimensions of the classroom until after session 2 where objects are interactive, then they started to be curious and looked around in session 3 to see if any more changes would happen. One of the curious actions was to see if the clock was actually running. 26% stayed completely focused on the lecture. 11% said they became bored in session 3 and got carried away. One person (5%) mentioned that they did not like the teacher avatar so they looked away.

5.1 Limitations

The study results and feedback has provided interesting insight and challenge to the current study design and also could raise discussions for other similar works. Although there are several significant differences in the observed variables while the eye behaviors seem not to be highly correlated, the results are not conclusive. It indicated that using a between-subject experimental design is not enough to draw a conclusion on the effectiveness of attention training. A more rigorous control group comparison will be needed to refine the study, figuring out the situations that whether the training session with the interactions has caused more excitement and emotional arousal, and it could also lead to making use of the interactions for attention training.

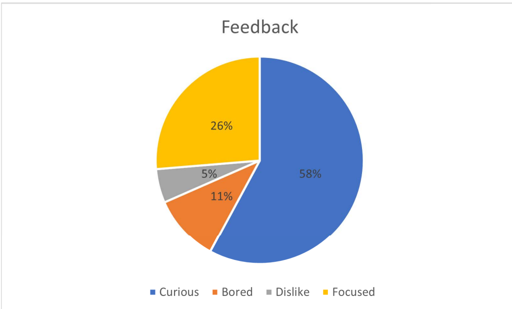


Figure 10: Follow-up interview feedback

6 Conclusion and Future Work

To sum up, we have introduced the detailed design and developed a system prototype for VR attention training therapy. An eye gazing determination methodology and a virtual objects hierarchy for attention training have been implemented. A preliminary user study has been conducted to test the effectiveness of the methodology of eye gazing attention determination. A total of 20 participants have taken the experiment. Each of them went through the entire three sessions with one of the four training strategies. The results show that eye-gazing attention determination methodology can effectively detect users' eye-gazing attention, and the change in pupil diameters and eye openness are not strongly correlated with attention changes. The average distracted time on a few objects is significantly different in session 1 and session 3. Although, since the results were obtained in a relatively small group, the correlation may not be conclusive. Since this is a preliminary study with typically developed individuals, the collected samples are in the plan to compare to the same amount of individuals with ASDs - the target audience of the study. We expect it will produce more interesting results for the following reasons: 1) Stimuli are often more intense for individuals with ASD, thus more intense GSR and HR are expected to be recorded and 2) adding "unwanted" stimuli could potentially have a different effect on individuals with attention impairment. The collected GSR and HR will be processed with data analytics models for comparison. With the expectation that the system does show improvement for our sample subjects in attention training, we will seek to collaborate with clinical facilities for more clinical-standard studies and apply a better utilization of the system.

It is expected that this study will generally benefit researchers, educators, and students with special needs. By taking advantage of VR in assisting training, the research team aims to provide a relatively low-cost and fun approach to the treatment of attention deficit.

Acknowledgments

This work was supported in part by a grant from the National Science Foundation (Award # 1850438).

References

[1] E. Birmingham and A. Kingstone, "Human Social Attention," *Annals of the New York Academy of Sciences*, vol. 1156, no. 1, pp. 118–140, 2009. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1749-6632.2009.04468.x

[2] C. Lord, M. Elsabbagh, G. Baird, and J. Veenstra-Vanderweele, "Autism spectrum disorder," *The Lancet*, vol. 392, no. 10146, pp. 508–520, Aug. 2018. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0140673618311292

[3] C. M. McMahon, M. D. Lerner, and N. Britton, "Group-based social skills interventions for adolescents with higher-functioning autism spectrum disorder: a review and looking to the future," *Adolescent Health, Medicine and Therapeutics*, vol. 4, pp. 23–38, Jan. 2013. [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3744120/

[4] C. Mei, B. T. Zahed, L. Mason, and J. Ouarles, "Towards Joint Attention Training for Children with ASD - a VR Game Approach and Eye Gaze Exploration," in *2018 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)*, Mar. 2018, pp. 289–296.

[5] Z. Li and C. Zhang, "A Review of Immersive Virtual Reality in Special Education," in *2022 Proceedings of the EDSIG Conference*, vol. 8, no. 5826, Clearwater, FL, 2022, p. 14. [Online]. Available: https://proc.iscap.info/2022/pdf/5826.pdf

[6] J. Zhang, M. Mullikin, Y. Li, and C. Mei, "A Methodology of Eye Gazing Attention Determination for VR Training," in *2020 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW)*, Mar. 2020, pp. 138–141.

[7] CDC, "Data and Statistics on Autism Spectrum Disorder | CDC," Mar. 2022. [Online]. Available: https://www.cdc.gov/ncbddd/autism/data.html

[8] ——, "Autism Spectrum Disorder (ASD) | CDC," Aug. 2022. [Online]. Available: https://www.cdc.gov/ncbddd/autism/index.html

[9] L. Bozgeyikli, A. Raij, S. Katkoori, and R. Alqasemi, "A Survey on Virtual Reality for Individuals with Autism Spectrum Disorder: Design Considerations," *IEEE Transactions on Learning Technologies*, vol. 11, no. 2, pp. 133–151, Apr. 2018. [Online]. Available: https://ieeexplore.ieee.org/document/8010470/

[10] A. Dechsling, S. Orm, T. Kalandadze, S. Sütterlin, R. A. Øien, F. Shic, and A. Nordahl-Hansen, "Virtual and Augmented Reality in Social Skills Interventions for Individuals with Autism Spectrum Disorder: A Scoping Review," *Journal of Autism and Developmental Disorders*, Nov. 2021. [Online]. Available: https://doi.org/10.1007/s10803-021-05338-5

[11] L. Zhang, J. Wade, A. Swanson, A. Weitlauf, Z. Warren, and N. Sarkar, "Cognitive state measurement from eye gaze analysis in an intelligent virtual reality driving system for autism intervention," in *2015 International Conference on Affective Computing and Intelligent Interaction (ACII)*, Sep. 2015, pp. 532–538, iSSN: 2156-8111.

[12] D. Bian, J. W. Wade, L. Zhang, E. Bekele, A. Swanson, J. A. Crittendon, M. Sarkar, Z. Warren, and N. Sarkar, "A Novel Virtual Reality Driving Environment for Autism Intervention," in *Universal Access in Human-Computer Interaction. User and Context Diversity*, C. Stephanidis and M. Antona, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2013, pp. 474–483.

[13] "E4 wristband | Real-time physiological signals | Wearable PPG, EDA, Temperature, Motion sensors." [Online]. Available: https://www.empatica.com/research/e4

[14] D. Premack, "Toward empirical behavior laws: I. Positive reinforcement," *Psychological Review*, vol. 66, pp. 219–233, 1959, place: US Publisher: American Psychological Association.

[15] B. A. Iwata, "Negative Reinforcement in Applied Behavior Analysis: An Emerging Technology," *Journal of Applied Behavior Analysis*, vol. 20, no. 4, pp. 361–378, 1987. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1901/jaba.1987.20-361

[16] J. Hockenhull and E. Creighton, "Training horses: Positive reinforcement, positive punishment, and ridden behavior problems," *Journal of Veterinary Behavior*, vol. 8, no. 4, pp. 245–252, Jul. 2013. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1558787812000950

[17] J. Crosbie, "Negative Reinforcement and Punishment," in *Handbook of Research Methods in Human Operant Behavior*, ser. Applied Clinical Psychology, K. A. Lattal and M. Perone, Eds. Boston, MA: Springer US, 1998, pp. 163–189. [Online]. Available: https://doi.org/10.1007/978-1-4899-1947-2_6