Proceedings of the 2023 International Conference on Machine Learning and Automation
DOI: 10.54254/2755-2721/35/20230395

Research on user response in virtual reality environment based on visualization and clustering

Long Gao

College of Letters and Science, University of California, Santa Barbara, CA 93106, United States

longgao@ucsb.edu

Abstract. As the feasibility of virtual reality (VR) therapies is gradually being validated, understanding users' physiological and emotional responses to different VR environments is crucial for optimizing VR experiences and improving user engagement. This study aims to introduce machine learning models to analyze user responses to VR environments and identify user groups with similar physiological and emotional characteristics. This study employs visualization tools and clustering models to explore the role of various factors in shaping user experience. K-Means modeling helps the research team understand users' physiological and emotional responses to VR environments. The Principal Component Analysis (PCA) dimensionality reduction algorithm makes the model visualization easier to understand and implement. This study is conducted on a virtual reality experience dataset and produced many nuanced users experience results. The results of the experiments show that there is an apparent disparity in the experience of VR among users of different age groups. It also shows that different user groups have different levels of suitability for VR. Targeted improvements to VR can provide suggestions for people with different needs. This study has significant implications for analyzing and understanding the emotional responses and preferences of VR users and driving the personalization of VR products.

Keywords: virtual reality, emotional response, Principal Component Analysis, K-Means clustering.

1. Introduction

Virtual Reality (VR) describes technology that immerses users in a sensory-stimulating virtual environment. At its core, VR technology creates interactive, three-dimensional computer-generated environments that replicate real-world experiences [1]. In recent years, VR technology has become a transformative technology beyond entertainment and gaming uses. It is increasingly used to treat neurological and psychiatric disorders, including depression, anxiety, and other emotional abnormalities [2]. Research has shown that VR technology transcends the physical limitations of traditional therapies and opens up new possibilities for treatment [3]. From assisting with exposure therapy, recovering from neurological disorders, and promoting emotional well-being, VR technology has demonstrated its potential as a versatile and powerful tool in mental health and healthcare [4]. Continued exploration of VR applications holds the potential to enhance the overall well-being and quality of life for numerous

DOI: 10.54254/2755-2721/35/20230395

individuals worldwide. As such, this paper suggests approaches for enhancing VR design through the comprehension of users' physiological and emotional reactions to various VR environments.

Numerous psychological obstacles hinder the adoption of medication-assisted treatment, stemming from the societal stigma and the weight of medication linked to mental health disorders. Mental health stands as a representative domain within which VR technology holds the potential for diagnosing and addressing a range of mental disorders [5]. During the 1990s, Rothbaum et al. conducted a study showcasing the efficacy of VR in addressing agoraphobia among college students [6]. Subsequently, a burgeoning interest in employing VR for psychotherapy emerged. Starting from the inauguration of the first VR clinic in South Korea in 2005, catering to individuals with schizophrenia, social phobia, and alcohol addiction, numerous establishments have turned to VR-based interventions for conditions such as dementia, post-traumatic stress disorder (PTSD), and online gaming disorder (IGD) [5]. In July 2019, VR-based cognitive-behavioral therapy (CBT) for social phobia achieved recognition as an innovative medical technology. A meta-analysis conducted by Powers et al. determined that individuals in the VR group experienced enhanced treatment outcomes compared to those undergoing real-world exposure therapy [7]. An additional meta-analysis revealed that VR exhibited effectiveness in treating amnestic mild cognitive impairment (MCI) and early to moderate Alzheimer's disease by leveraging cognitive reserve and training techniques. New research on VR has also emerged in other fields. VR can potentially enable elderly individuals to gradually acclimate to unfamiliar environments, thus mitigating the adverse impacts of place attachment and social exclusion [8]. Furthermore, a pioneering intervention that combines artificial intelligence and virtual reality (AI-VR) was employed to address hot flashes in women aged 18 to 60 diagnosed with breast or ovarian cancer [9]. Artificial intelligence helps personalize the experience through algorithms driven to ensure that all aspects of patient engagement are utilized.

The main objective of this paper is to introduce machine learning models to build classifiers to understand users' physiological and emotional responses to different VR environments. This leads to improved VR design, user comfort, and customization. Specifically, first, visualization tools are used to analyze the specific distribution and detailed data information of different influencing factors, including Age, Gender, VR Headset, Duration, Motion Sickness, and Immersion Level. Second, by controlling variables to generate comparative images, the study determines the direct relationship between each two-factor combination. In addition, Principal Component Analysis (PCA) and K-Means are used to comprehensively analyze how different genders, ages, and VR Headsets affect duration, motion sickness, and immersion levels. Meanwhile, the relationship between Duration, Motion Sickness, and Immersion Level is also compared. The results show that users who use VR for less than 20 minutes have lower levels of immersion. The older the user, the longer the duration and the higher the immersion level. 30-36 years old men, 32-35 years old women, and 34-40 years old others experience higher levels of immersion. Also, the HTC Vive is best suited for users under 30, the Playstation VR is best suited for 30-50 years old, and the Oculus Rift is best suited for those over 50. The study analyzes in detail the impact of specific age groups, gender, and time spent immersed on VR effectiveness. It can provide recommendations for people with different needs.

2. Methodology

2.1. Dataset description and preprocessing

The Virtual Reality Experiences dataset from Kaggle [10] contains 1,000 pieces of data with seven variables. The UserID functions as a distinctive identifier for each user engaged in the VR experience. Age records the participant's age during the VR encounter. Gender signifies the user's sex and can include classifications like "Male," "Female," or "Other." VRHeadset designates the particular VR headset employed by the user during the VR experience, encompassing options like "Oculus Rift," "HTC Vive," and "PlayStation VR." Duration indicates the time (in minutes) the user spends in the virtual reality environment. MotionSickness denotes the self-reported motion sickness rating of the user throughout the VR experience, using a scale of 1 to 10 where higher values signify more pronounced motion sickness. ImmersionLevel gauges the participant's sense of immersion during the VR experience. It captures the user's subjective perception of immersion on a scale of 1 to 5, with 5 denoting the utmost level of immersion. Only the category UserID is dropped from the dataset for subsequent visualization and inter-variable analysis and comparison.

2.2. Proposed approach

The main goal of this study is to analyze the VR experience dataset through step-by-step complex visualization and classification models to improve the VR design and allow better experience results and customization for users or patients treated with VR technology. Following the process shown in Fig. 1, visualization tools first perform the analysis. By looking at individual distributions and information on variables such as Age, Gender, VR Headset, Duration, Motion Sickness, and Immersion Level, the basics can be captured in preparation for subsequent comparative modeling. Secondly, direct relationships between variables are obtained by drawing pairwise plots with control variables. The study clearly shows how the factors affecting VR interact by comparing the results in detail. In addition, using correlation clustering models such as PCA and K-Means allows for a more comprehensive analysis of image distributions and comparisons between different variables. This range of models, from simple to complex, allows the study to analyze the data in a step-by-step manner and allows the study to demonstrate the differences between the models.

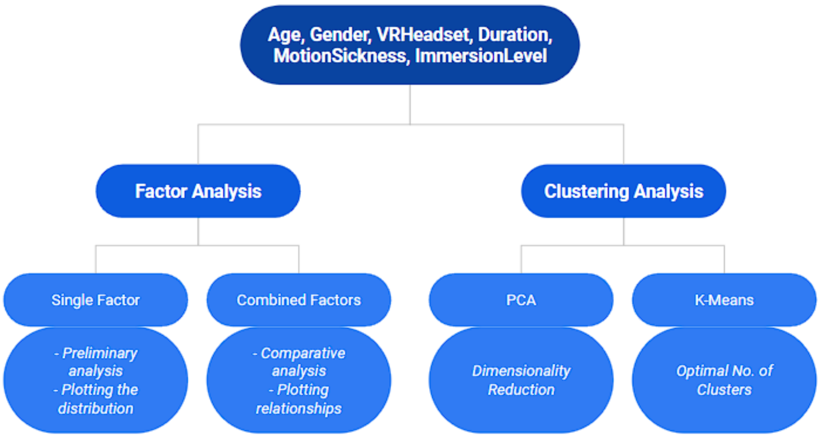

Figure 1. Flow chart process.

2.2.1. Factor analysis. Starting with the analysis of individual factors in the dataset is a necessary starting point for subsequent research. To comprehensively analyze the VR dataset's factors and facilitate the acquisition of essential insights, this study employs a range of visualization techniques, including pie charts, bar charts, and histograms. A pie chart visualizes the distribution of categorical data as proportional segments of a whole. It is ideal for illustrating different categories' composition or relative proportions within a dataset. A bar chart employs rectangular bars to display categorical or numerical data across different categories. Bar charts effectively compare data values between categories and reveal trends or variations. Histograms are particularly useful for understanding the distribution and frequency of data across a continuous range. Moreover, these visualizations make it easier to detect outliers, identify clusters, and observe variations that might not be apparent in raw data.

The process of contrasting data and comparing images is critical in this research. The study meticulously records five different image sets, each consisting of four contrasting line plot images, holding control variables constant. For each line plot image, the study selects two factors to be compared. These factors can be Age, Gender, VRHeadset, or any other relevant variables within the dataset. Within each figure, the study simultaneously draws five lines on the line plot, each representing a different Immersion Level category (e.g., 1 to 5). These lines depict how the selected factors influence users' responses at various levels of immersion. By holding control variables constant, the study ensures that any observed variations can be attributed to the factors being compared. Viewers can easily compare how users' responses change across different levels of Immersion Level for various combinations of factors. This facilitates making meaningful inferences about the impact of different factors on users' experiences.

2.2.2. Clustering analysis. The goal of the clustering analysis is to identify natural groupings of users with similar physiological and emotional responses to different VR environments. To accomplish this, the study utilizes the K-Means clustering algorithm, a well-established and effective unsupervised learning technique. Considering a collection of observations $(x_1, x_2, \ldots, x_n)$, where each observation is a d-dimensional real vector, the K-Means clustering technique strives to divide the n observations into k (where k $\leqslant$ n) groups denoted as $S = \{S_1, S_2, \ldots, S_k\}$. The primary goal is to minimize the within-cluster sum of squares (WCSS), which essentially corresponds to the variance. In formal terms, the objective involves determining:

$$\mathbf{arg\,min}_{S} \sum_{i=1}^{k} \sum_{x \in S_i} \|x - \mu_i\|^2 = \mathbf{arg\,min}_{S} \sum_{i=1}^{k} |S_i|\, Var\, S_i \qquad (1)$$

where μ_i is the mean (also called centroid) of points in S_i, i.e. $\mu_i = \frac{1}{|S_i|}\sum_{x \in S_i} x$, $|S_i|$ is the size of S_i, and $\|\cdot\|$ is the usual L^2 norm. This is tantamount to minimizing the squared deviations between pairs of points within the same cluster:

$$\arg\min_{S} \sum_{i=1}^{k} \frac{1}{|S_i|} \sum_{x,y \in S_i} \|x - y\|^2 \qquad (2)$$

Choosing the appropriate number of clusters (k) is crucial for obtaining meaningful clustering results. This study employs the elbow method to ascertain the optimal number of clusters. The elbow method entails plotting the explained variance against the number of clusters (k) and identifying the point of inflection, often referred to as the "elbow," in the graph. The elbow point indicates the optimal number of clusters at which the variance explained begins to level off, suggesting diminishing returns as k increases. Fig. 2. shows an example:k=7.

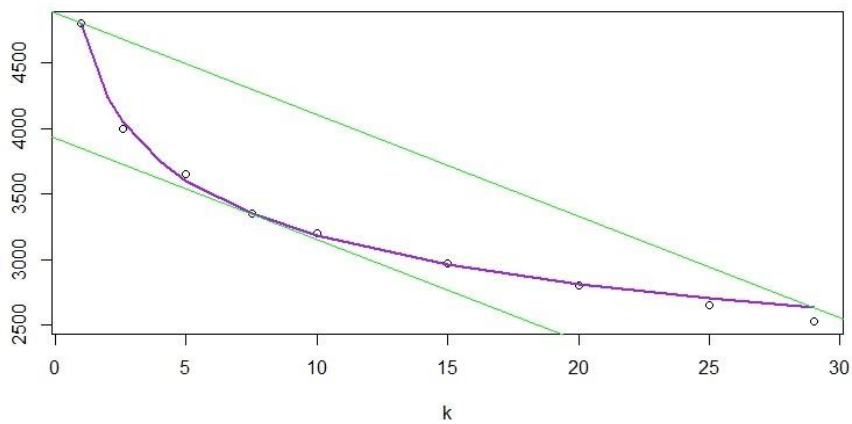

Figure 2. Elbow method.

2.2.3. PCA. PCA is a widely used method for analyzing extensive datasets encompassing numerous dimensions or features per observation. It aims to enhance the interpretability of data while preserving a substantial portion of its information content and facilitates the visualization of multidimensional data. Functioning as a statistical approach, PCA reduces the complexity of a dataset's dimensions. This is

DOI: 10.54254/2755-2721/35/20230395

achieved through a linear transformation of the data into a fresh coordinate system, wherein a majority of the data's variations can be effectively described using fewer dimensions compared to the original data representation. Since the Virtual Reality Experiences dataset contains multiple features, it is not easy to visualize the clustering results directly. Therefore, the study uses PCA for dimensionality reduction. PCA executes a transformation on multidimensional data, effectively projecting it into a space with fewer dimensions, all the while retaining the majority of the variance that was present in the original data. By plotting the PCA-transformed data, the study visualizes user groupings in two dimensions. While PCA may not capture all the nuances of the data, it provides valuable visualizations for evaluating clustering results. Fig. 3 below demonstrates how PCA improves the clustering image for the dataset of this study.

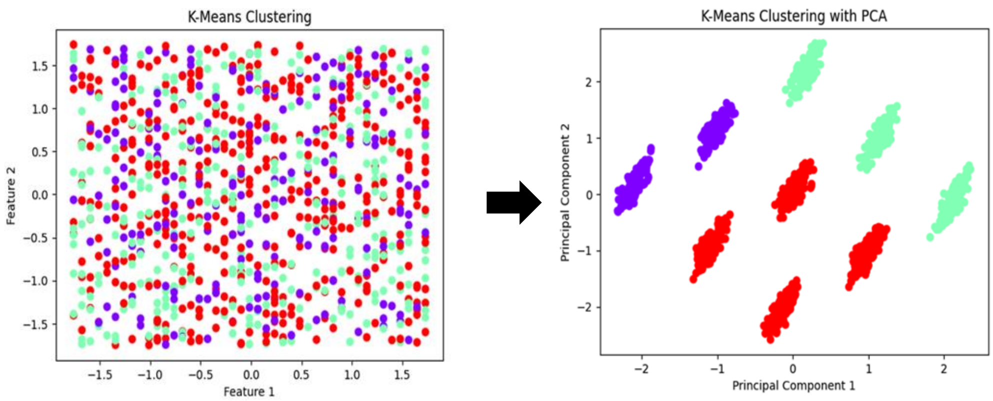

Figure 3. Dimensionality reduction.

2.3. Implemented details

The study employs a combination of tools, including Jupyter Notebook, NumPy library, Matplotlib library, Seaborn library, and Scikit-Learn library, to carry out visualizations and implement clustering models. The experimentation is conducted on a Windows 11 laptop powered by an AMD Ryzen 9 5900HS with Radeon Graphics running at 3.30 GHz and NVIDIA GeForce RTX 3060. For the K-Means and PCA analyses, the following settings are utilized: The elbow method aids in identifying an optimal value that strikes a balance between within-cluster variance and the number of clusters. To initialize the initial positions of cluster centroids, the study adopts the "k-means++" method, which is the default initialization method in the scikit-learn library. Moreover, PCA condenses the dataset into two dimensions, facilitating visualization.

3. Result and discussion

The results of the analysis provide valuable insights into the factors that influence users' physiological and emotional responses to different VR environments. This paper discusses critical findings related to Age, Gender, VR Headset, Duration, Motion Sickness, and their implications for user Immersion Level and experience.

Fig. 4 is an example of the analysis of age. It reveals that most users fall within the 30-40 age range. Interestingly, users in this age group also report the highest immersion levels. This suggests that individuals in their 30s and 40s tend to have a more immersive experience in VR environments.

DOI: 10.54254/2755-2721/35/20230395

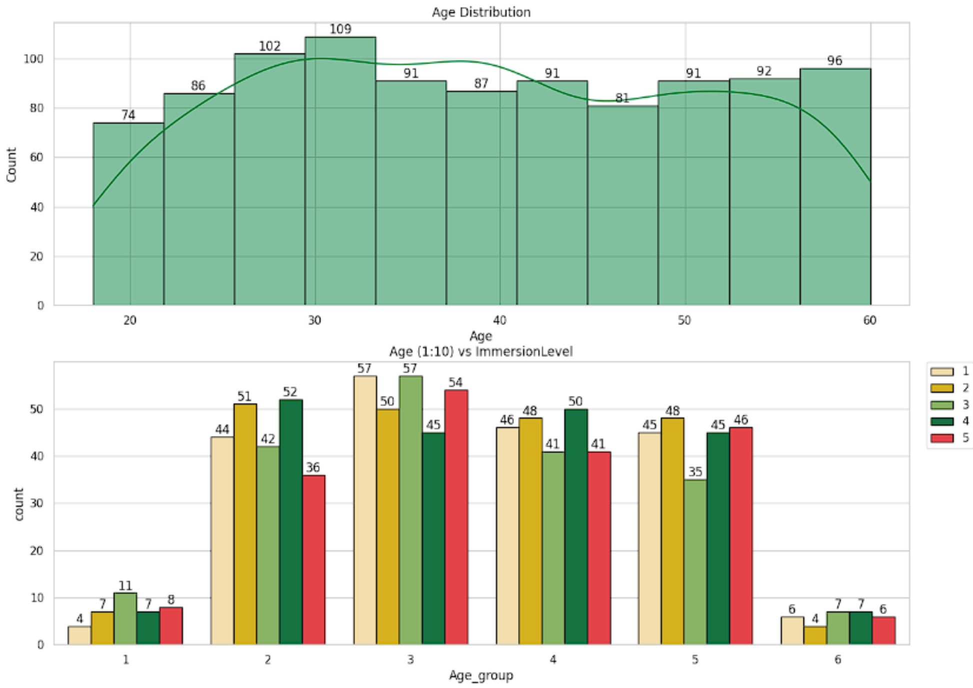

Figure 4. The analysis of age (histogram and count plot respectively).

Fig. 5 the Gender-based analysis showcases males and females exhibit comparable levels of immersion, with each gender having almost the same number of participants. Notably, males tend to experience higher immersion levels when using VR. Conversely, for females and other gender categories, Immersion Levels 1 and 2 are more prevalent, possibly indicating differences in user preferences and sensitivities.

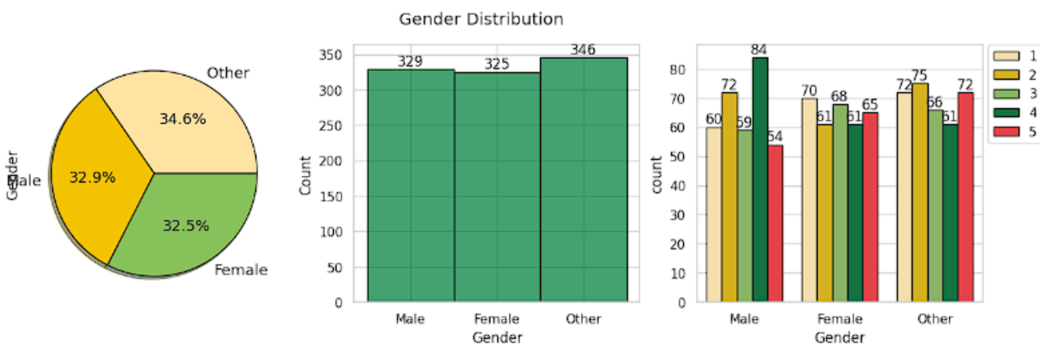

Figure 5. The analysis of gender (pie chart, histogram, count plot respectively).

Users predominantly favor the Oculus Rift VR headset, reporting the best experience. The analysis suggests that VR headset choice significantly affects user immersion. This finding underscores the importance of selecting the appropriate VR hardware to enhance user engagement and satisfaction. Duration emerges as a critical factor affecting immersion. Users with durations below 20 minutes tend to have lower immersion levels, whereas longer durations correspond to higher ones. This suggests that more prolonged exposure to VR environments leads to a more immersive experience. Additionally, Oculus Rift stands out as providing the best experience for shorter (<10 minutes) and longer (>40 minutes) durations, while HTC Vive performs well within the 10-40 minutes range. Motion sickness directly impacts immersion levels. Higher motion sickness ratings are associated with lower immersion rates. This finding underscores the importance of addressing motion sickness-related challenges to enhance user immersion and overall VR experience.

Fig. 6 shows one of the K-Means (k = 4) images drawn by PCA dimensionality reduction to reduce the dataset to two dimensions. The clustering reaffirms that the 30-40 age group forms the majority of users. Moreover, clusters reflecting gender distribution corroborated earlier findings, indicating an equitable representation of genders. Clusters center around VR headset choices aligned with prior results, showcasing Oculus Rift as the most popular choice and attributing the best experiences to it. Clusters associated with duration reaffirm earlier observations. Users with shorter durations under 20 minutes generally report lower immersion levels, while those who engage for more extended periods note heightened immersion. Clusters tie to motion sickness highlights the inverse relationship between the two. Higher motion sickness ratings are consistently linked to lower immersion levels, affirming that minimizing motion sickness is crucial for optimizing user immersion. In summary, the integrated approach of K-Means clustering and PCA reaffirms and enriches understanding of users' VR experiences.

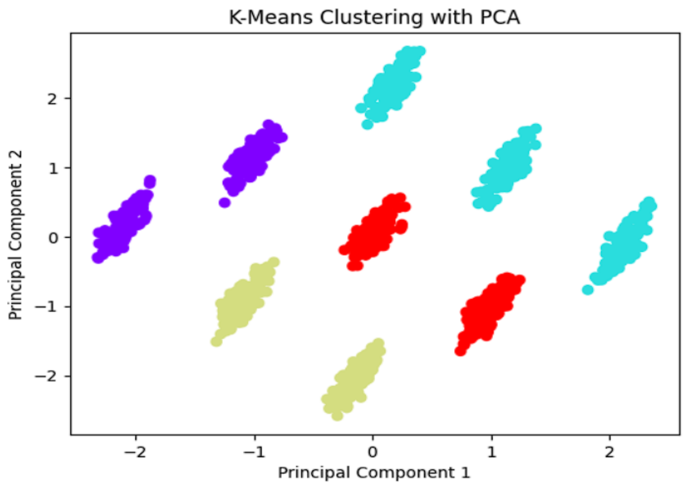

Figure 6. Clustering analysis.

The insights garnered from this study have substantial implications for VR environment design and user engagement strategies. Tailoring experiences based on factors such as Age, Gender, and VR Headset choice can contribute to heightened immersion levels and user satisfaction. Further research could delve into the intricate connections between these factors to develop more precise and personalized user profiles.

4. Conclusion

This study aims to introduce machine learning models to recognize users' physiological and emotional responses to different VR environments. VR design can be improved by understanding the different sensory characteristics of users. The study first visualizes and analyzes various data distributions to compare the relationship between different factors. Second, the study achieves this through a two-step analysis method. One aspect of the analysis involves the application of the K-Means clustering algorithm, which serves the purpose of identifying clusters of users exhibiting analogous physiological and emotional responses. The ideal number of clusters is ascertained through the utilization of the elbow method. Furthermore, on the other side, the study uses PCA for downscaling and visualization. The clustering is observed in a low-dimensional space. Experimental results show that K-mean clustering successfully identifies natural groupings of users based on their physiological and emotional responses to different VR environments. PCA visualization provides valuable insights into clusters' spatial distribution, revealing user experience patterns. In the future, this study plans to target user engagement

DOI: 10.54254/2755-2721/35/20230395

as the next research phase. The study will focus on analyzing the factors that influence user engagement with VR environments. The research aims to unite more features with clustering to create a more comprehensive user profile. In addition, the research will investigate the role of interaction patterns and environmental factors in shaping the user experience in order to improve the overall design of VR environments.

References

[1] Schultheis M T Rizzo A A 2001 The application of virtual reality technology in rehabilitation Rehabilitation Psychology 46(3): pp 296–311

[2] Maples-Keller J L Bunnell B E Kim S J Rothbaum B O 2017 The Use of Virtual Reality Technology in the Treatment of Anxiety and Other Psychiatric Disorders Harv Rev Psychiatry 25(3): pp 103-113

[3] Salib V 2023 Exploring Virtual Reality Exposure Therapy in Mental Healthcare LifeSciencesIntelligence

[4] North M M North S M 2016 Virtual reality therapy In Computer-assisted and web-based innovations in psychology, special education, and health pp. 141-156

[5] Kim S Kim E 2020 The Use of Virtual Reality in Psychiatry: A Review Soa Chongsonyon Chongsin Uihak 31(1): pp 26-32

[6] Rothbaum B O Hodges L F Kooper R Opdyke D Williford JS North M 1995 Effectiveness of computer-generated (virtual reality) graded exposure in the treatment of acrophobia Am J Psychiatry 152(4): pp 626-628

[7] Powers M B Emmelkamp P M 2008 Virtual reality exposure therapy for anxiety disorders: A meta-analysis J Anxiety Disord 22(3): pp 561-569

[8] Zhai K Dilawar A Yousef M S Holroyd S El-Hammali H Abdelmonem M 2021 Virtual Reality Therapy for Depression and Mood in Long-Term Care Facilities Geriatrics (Basel) 6(2):p 58

[9] Horesh D Kohavi S Shilony-Nalaboff L Rudich N Greenman D Feuerstein JS Abbasi MR 2022 Virtual Reality Combined with Artificial Intelligence (VR-AI) Reduces Hot Flashes and Improves Psychological Well-Being in Women with Breast and Ovarian Cancer: A Pilot Study Healthcare (Basel) 10(11): p 2261

[10] 2023 Virtual Reality Experiences https://www.kaggle.com/datasets/aakashjoshi123/virtual-reality-experiences