worked, rehabilitation accordingly is somewhat difficult. We proposed a rehabilitation method in a highly immersive VR environment that can complement existing cognitive-behavioral therapy.

Methods: In this study, VR contents were produced based on the rehabilitation scenario for panic disorder patients created by the Gachon Gil Hospital Psychiatry. In order to utilize VR content characteristics that experience virtual environments with high immersion, the plaza horror-based scenario was used, and the pain was gradually increased from 1 to 5 in a total of five stages. Clinical demonstration using Sheehan Disability Scale (SDS) was conducted on 20 ordinary people and 40 patients to see if the produced VR content was effective in rehabilitation of panic disorder. SDS is a survey that assesses dysfunction in the main living areas of life. Data collection was conducted before the first stage 1 clinical trial and after the stage 5 clinical trial, and repeated measurement ANOVA was performed using the collected data.

Results: We found that there were significant differences in the rehabilitation methods for each group's pre- and post-clinical differences. Based on the survey score, in the case of the general population, the average value fell from 0.1 to 0.0 before and after the clinical trial, and the patient group decreased from 13.7 to 11.3. This means that the degree of dysfunction has decreased, which shows a recovery. We confirmed that these results were statistically significant ($F = 15.672$, $P < 0.01$).

Table 1. Clinical results using SDS.

Group	SDS (Mean ± SD)		*F*(*P*-value)		
	Before(Be)	After(Af)	Group	Time	Group × Time
Patient (A)	13.7 ± 7.6	11.3 ± 7.5		15.672** (.001) Be>Af	
Normal (B)	0.1 ± 0.5	0.0 ± 0.0		1.000 (.332) Be=Af	
F or t	7.299**	6.172**	50.167**	13.861**	12.484**
p-value	.000	.000	.000	.001	.001
Comparison	A>B	A>B			

**$P < 0.01$; *$P < 0.05$

Conclusions: The proposed method was found to complement existing cognitive behavioral therapy methods for panic disorder patients. It is expected that patients will be able to perform rehabilitation on a regular basis without visiting the hospital in the future.

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LA07 | ExpDNN4BC: Explainable deep neural network for breast cancer

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Objectives: This study used the Breast Cancer Coimbra Data Set from the UCI (University of California, Irvine) Machine Learning Repository to analyze multivariates, including x_1 (age), x_2 (BMI, body mass index), x_3 (glucose), x_4 (insulin), x_5 (HOMA, homeostasis model assessment), x_6 (leptin), x_7 (adiponectin), x_8 (resistin), x_9 (MCP-1, monocyte chemoattractant protein 1), for the classification of breast cancer patients and healthy controls. Patrício et al. (2018) did the univariate analysis to extract the features of resistin, glucose, age and BMI, and presented the area under curve (AUC) value of 0.91 based on support vector machine (SVM). Although some features could be extracted based on univariate analysis, the input interaction effects have not been investigated.

Methods: An explainable deep neural network (ExpDNN) which enhances the explanatory power of neural network can be used to generate an important level list of variables for feature extraction. An ExpDNN for Breast Cancer (ExpDNN4BC) is proposed to extract the features of breast cancer. The extracted features can be adopted as the inputs of a deep neural network to classify the breast cancer patients and healthy controls.

Results: In our experimental results, the important level list of variables is sorted in accordance with the explainable layers is x_6, x_7, x_1, x_8, x_3, x_5, x_9, x_4 and x_2. In the case considering top 7 variables (i.e. leptin, adiponectin, age, resistin, glucose, HOMA and MCP-1), the AUC value of the deep neural network with three hidden layers is improved from 0.91 to 0.9643. The results showed that the AUC value could be improved without considering insulin and BMI. Although the BMI might be an important feature in accordance with univariate analysis, the input interaction effects of the top 7 variables extracted by ExpDNN are relatively significant.

Conclusions: The proposed ExpDNN4BC can extract critical features and improve AUC values for the classification of breast cancer patients and healthy controls.