

Adaptive Virtual Reality Exposure Therapy Using AI-Driven Anxiety Prediction from Physiological and Behavioral Data

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Abstract—All mental health disorders; anxiety disorders rank as the most common ones. They affect the cognitive functions of an individual as well as their ability to socialize or live in a quality manner. Exposure Therapy happens to be one of the most effective methods aimed at treating fears, phobias, and traumatic memories; however, the traditional approach to exposure therapy and VRET is unable to modify the exposure intensity in accordance with the situation that is occurring with the patient, thus making this method ineffective. This article suggests a solution to the problem by creating AVRET, or Adaptive Virtual Reality Therapy, which will provide the opportunity to predict the anxiety of the patient in real-time through their physiological (HR, HRV, GSR) and behavioral (eye-tracking, blink rate, pupil dilation) indicators. The suggested system uses an LSTM deep learning model to evaluate the amount of anxiety and change the scenario, distance to objects, sounds, or level of difficulties based on the current anxiety evaluation.

Keywords—Virtual reality exposure therapy; LSTM; anxiety prediction; physiological computing; closed-loop systems; multimodal fusion

I. INTRODUCTION

A cause of concern in the healthcare system is anxiety disorders that affect emotional well-being, cognitive abilities, and interpersonal relationships. Standard treatments for anxiety disorders include cognitive behavioral therapy (CBT) and exposure therapy; however, traditional exposure therapy does not have complete control over the environment, relies on the therapist's thorough assessment of the patient's condition, and does not provide tailored service, in addition to creating safety problems [1]. Virtual reality exposure therapy (VRET) overcomes some of the problems identified in traditional therapy by providing a safe environment for patients to practice the skills they acquired in therapy. Although VR exposure therapy has proved treatment effective, many of the existing systems remain rigid and unable to respond to the patient's physiological signals to adapt to the effectiveness of treatment. Advances in AI, deep learning, and physiological computing now allow emotional state to be inferred from signals such as heart rate (HR), heart rate variability (HRV), galvanic skin response (GSR), pupil diameter, eye tracking, eye blink rate, and motion.

This study proposes a closed-loop Adaptive VR Exposure Therapy (AVRET) framework that combines multimodal physiological sensing, behavioral analysis, LSTM-based

anxiety prediction, and adaptive VR control with real-time feedback. An LSTM network extracts temporal patterns from the multimodal stream to estimate anxiety, and the adaptive controller uses this estimate to continuously tune scene complexity, object motion, loudness, and exposure level, improving personalization, comfort, safety, and interactivity relative to static VR therapy [2].

This research proposes a closed-loop intelligent healthcare framework combining physiological monitoring, behavioral analysis, deep-learning-based emotion assessment, adaptive VR control, and feedback, aimed at maximizing patient emotional comfort during therapy [3].

The main contributions of this work are: 1) A multimodal physiological and behavioral sensing approach for real-time anxiety measurement; 2) Integration of HR, HRV, GSR, eye-tracking, blink frequency, pupil dilation, and motion for holistic emotional awareness; 3) An LSTM-based deep learning model for temporal anxiety prediction; 4) A closed-loop VR controller that modifies the environment based on emotional state; 5) Improved personalization, emotional safety, and adaptive interaction in immersive healthcare; and 6) An AI-powered intelligent mental healthcare framework combining VR and deep learning.

II. LITERATURE SURVEY

A. Prevalence and Exposure Therapy

Anxiety disorders affect an estimated 301 million people worldwide (WHO, 2023), including GAD, panic disorder, social anxiety disorder, specific phobias, agoraphobia, and PTSD, and account for 28.6 million DALYs annually [4]. In the United States alone, direct and indirect costs exceed \$42 billion per year, yet fewer than 40% of patients receive effective treatment due to shortages of specialists, cost, stigma, and limited access [5].

Exposure therapy is still the standard treatment according to the reciprocal inhibition theory of Wolpe as well as modern models of inhibitory learning. The key factor behind the effectiveness of this technique is the intensity of the exposure, its performance without any attempts to escape the fear [6], and the level of predictability. However, application of the exposure method has a number of difficulties, such as real-world issues, lack of standardization, and thus reliance on subjective self-report tools, including the SUDS scale [7].

B. VRET and Physiological Affect Recognition

Virtual Reality Exposure Therapy (VRET), which was first created in the 1990s, allows the successful reproduction of real-life situations that provoke fear in a simulated 3-dimensional environment utilizing head-mounted displays and advanced techniques for tracking movements and spatial sounds, granting the doctor absolute control over the complexity and the intensity of the therapy process [8]. Reviews indicate the results of VRET are comparable to those obtained with in-vivo exposure, although it provides safety and accessibility for phobias, social anxiety, panic disorder, and PTSD. Nevertheless, the majority of existing systems are still based on rigid therapist-controlled procedures and have low adaptability towards rapid changes in users' emotional conditions.

It has been suggested that physiological computing can bridge the gap in anxiety and stress by activating the autonomic nervous system, bringing about measurable changes such as a rise in heart rate and a drop in heart rate variability, an increase in GSR (from normal skin conductance level and phasic responses), and changes in pupillary dilation, rate of blinking, and gaze pattern. Since no stand-alone solution has managed to capture the anxious state completely — cardiac signals are disturbed by motion; electrodermal measures have a slow response (and ocular signal changes are associated with attention) — using a combination of physiological signals can greatly direct the quest for an effective solution [9].

III. PROBLEM STATEMENT

Increasing stress, trauma, and lifestyle pressures have increased the rate of anxiety disorders, yet CBT and exposure therapy remain limited by dependence on therapists, poor scalability, and an inability to track patients' emotional state during treatment. VRET increases accessibility and control and has been used efficiently to treat phobias, PTSD, and social anxiety [10], but existing systems do not configure exposure to the patient's steadily changing emotional condition. Because emotional responses are highly individualized, static exposure risks either overexposure, increasing distress, or underexposure — limiting therapeutic effect. Furthermore, most anxiety-prediction approaches rely on a single physiological signal or offline analysis, limiting robustness, and common machine learning models struggle to capture long-term dependencies in physiological and behavioral data flow. These gaps motivate an Adaptive VR Exposure Therapy system that can track multiple modalities, predict anxiety in real time using deep learning, and adapt the environment continuously.

IV. PROPOSED MODEL

This study describes AVRET, a smart system for measuring a user's mood and making modifications to the VR environment based on the predicted level of anxiety. This is unlike traditional VR therapy, which uses preset conditions and relies on therapists, as AVRET automatically assesses physiological and behavioral parameters and adapts the environment in real-time using artificial intelligence [11]. Fig. 1 depicts a relevant closed-loop BCI VR setup whereby EEG is captured, feature extraction is done, and the classified state is returned to the user as visual, auditory, and haptic feedback. AVRET operates on the same closed-loop concept of

functioning but relies on peripheral physiological signals as opposed to central signals.

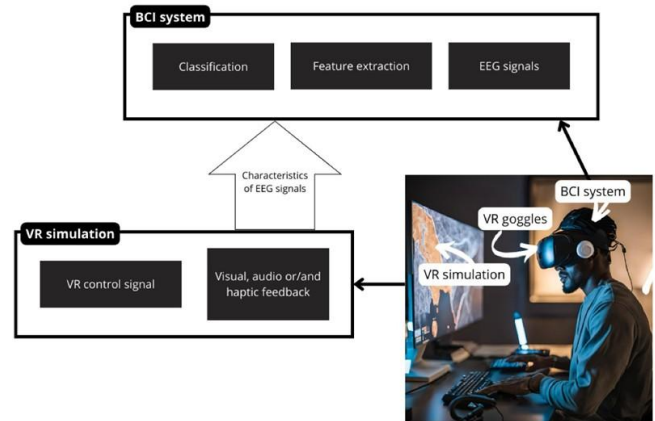


Fig. 1. Adaptive VR environment.

Fig. 2 shows the overall AVRET pipeline: User in VR Environment, Multimodal Sensor Input, Data Pre-processing, Feature Extraction, Multimodal Feature Fusion, LSTM-based Anxiety Prediction, Anxiety Classification, VR Adaptive Controller, VR Environment Adjustment, and a Feedback Loop.

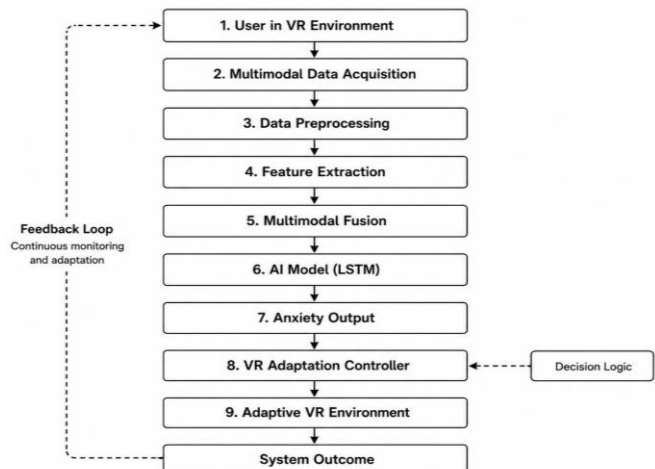


Fig. 2. Proposed adaptive virtual reality anxiety detection and adaptation pipeline.

The user is part of a virtual reality simulation (public speaking, crowds, heights, closed spaces, etc.) using head-mounted displays and motion tracking that enables emotional monitoring at any time. Multi-modal sensors continuously measure HR, HRV, GSR, eye-tracking, blink rate, pupil dilation, and head movement since anxiety, stress, and cognitive load occur simultaneously in multiple physiological systems. However, in order to use the raw signals, a number of processing techniques are applied to achieve proper filtering, smoothing, and alignment of the signals [12].

By extracting features, the latter signals can be converted into different statistical, temporal, and behavioral manifestations, such as mean/peak HR, HRV statistics, GSR peak attributes, blink frequency, pupil dilation change, fixation

time, and motion intensity. This way, cardiovascular, electrodermal, oculometric, and motion features are combined into a single emotional model using a fusion layer to make it more effective than one of the techniques [13]. The agreed features are then processed by the LSTM network that uses internal memory and does not analyze feature vectors like other models using the data multiplicity principle.

The level of anxiety predicted is sorted into Low, Medium and High and forwarded to the VR Adaptation Controller. In accordance with the level of anxiety, the VR adaptation controller alters the virtual environment accordingly: low level of anxiety – increases exposure intensity, medium level of anxiety – keeps the environment the same, high level of anxiety – lowers the stress level in the environment: scene complexity, lighting, object speed, sound, crowd density, stimulus object distance and exposure time are modified to reflect this adaptation. The process of continual monitoring leads to an adaptive approach which ensures the idea of personalization and the principle of comfort and safety of users. Constant feedback between monitoring, predicting, adapting, and re-evaluating proves that the system is more flexible as compared to static one-time VR therapy systems and methodologies [14].

V. METHODOLOGY

The AVRET framework proposed here is made of six stages as follows: obtaining the multimodal data, preprocessing the data, extracting features, combining the different modalities' features, performing anxiety prediction based on LSTM, and implementing a closed-loop adaptive VR control.

A. Data Acquisition, Preprocessing, and Key Formulas

In the process of virtual reality (VR) sessions, several multimodal physiological and behavioral signals are simultaneously collected in real time; these include the parameters of heart rate (HR), heart rate variability (HRV), reticular activation system (RAS), eye parameters (eye tracking), blink frequency, and pupil expansion. The captured data is filtered to remove noise, smoothed, excessive outliers removed, missing data filled in, and synchronized in time, ensuring a consistent format for analysis. Essential equations used for this purpose are as follows:

$$HR = 60 / RR \quad (RR = \text{interval between consecutive heartbeats})$$

$$HRV = \sqrt{[(1/N) \sum (RR_i - \text{mean}(RR))^2]} \quad \text{over } N \text{ samples}$$

$$GSR = SCL + SCR \quad (\text{tonic level} + \text{phasic response})$$

$$\text{Blink Rate} = \text{Number of Blinks} / \text{Time}$$

$$\text{Pupil Dilation (PD)} = P_{\text{current}} - P_{\text{baseline}}$$

$$\text{Normalization: } X_{\text{norm}} = (X - X_{\text{min}}) / (X_{\text{max}} - X_{\text{min}})$$

B. Feature Extraction and Fusion

Cardiovascular features consist of average/peak HR, RR-interval and HRV statistics, and frequency domain parameters; electrodermal features include skin-conductance level, GSR peak frequency, amplitude, and recovery; behavioral/ocular features include eye blink rate, pupil-dilation rate, fixation

duration, gaze pattern, and head-movement intensity. These are fused into a single vector, $F_{\text{fusion}} = [F_{\text{HR}}, F_{\text{GSR}}, F_{\text{Eye}}]$, improving emotional encoding, accuracy and robustness over any single modality.

C. LSTM Anxiety Prediction

An LSTM network predicts anxiety from the sequential multimodal features because it retains sequential dependencies via internal memory cells rather than treating each feature vector independently [16]. Its gating equations are:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \quad (\text{forget})$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (\text{input})$$

$$\tilde{C}_t = \tanh(W_c[h_{t-1}, x_t] + b_c) \quad (\text{candidate})$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \quad (\text{cell update})$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad (\text{output})$$

$$h_t = o_t \cdot \tanh(C_t) \quad (\text{hidden state})$$

The model is trained with cross-entropy loss, $\text{Loss} = -\sum y_i \log(\hat{y}_i)$, using the Adam optimiser with backpropagation-through-time and early stopping. The final anxiety-class probability is $A = \text{Softmax}(W_h h_t + b_h)$, related to Low, Medium, or High anxiety using thresholds T1 and T2 (Low: $A < T1$; Medium: $T1 \leq A < T2$; High: $A \geq T2$). Increased heart rate (HR) and decreased heart rate variability (HRV) are significant indicators of excitement and anxiety [15], and the LSTM tracks the speed of the occurrences of emotional changes, transitions, and different time intervals relating to stress from rising to recovery to compute anxiety intensity during virtual reality immersion [16].

D. Adaptive VR Control and Feedback

According to the level of anxiety predicted, the VR Adaptation Controller alters the complexity of the scene, speed of movement of the objects, sound level, density of crowd, time of exposure, brightness, distance of stimulus, and the difficulty in performing the tasks. It decreases the stimulation of the environment in case anxiety is high and gradually increases it in case anxiety is low, which ensures that the therapy maintains a stable emotional background. The feedback loop (physiological measurement $\rightarrow$ behavioral analysis $\rightarrow$ anxiety level prediction $\rightarrow$ adaptation of the VR to the patient $\rightarrow$ reassessment of the emotions of the patient) provides for the continuous operation of the system throughout the treatment process, which is not typical for the traditional therapy based on static models [17].

VI. EXPERIMENTAL SETUP

The evaluation of the experiment validated the AVRET framework for anxiety prediction accuracy, emotional responsiveness, adaptive VR effectiveness, deep learning performance, personalization capability, and system reliability.

The hardware involved a VR headset, cardiovascular and GSR sensors, an eye-tracking device, motion-tracking sensors, and a GPU-based workstation for the inference process.

The software used Python, TensorFlow/Keras for LSTM-based modeling, OpenCV for behavioral analysis,

NumPy/Pandas for signal processing, Matplotlib for visualization, and Unity/Unreal Engine for VR scene rendering.

A synchronized multimodal dataset consisting of HR, HRV, GSR, eye tracking, blink, pupil, and motion signals was acquired from VR sessions with different anxiety levels. The dataset was divided into training, validation, and testing datasets. Six VR scenarios were used where the stimulus was changed depending on the predicted level of anxiety.

Using the Adam optimizer, cross-entropy loss, backpropagation through time, cross-validation, and early stopping, the LSTM model was trained on multimodal feature windows in a particular order. Performance was measured through accuracy, precision, recall, F1-score, confusion-matrix analysis, and real-time response latencies. The adaptive VR controller was tested regarding its ability to alter the complexity of the environment, density of people in the hall, exposure duration, volume of sound, speed of object movement, and visual stimuli with regard to the level of anxiety compared to a commonly used (non-adaptive) VR therapy.

The experimental process involves user checking, turning on the sensors, going through collecting the data, processing the data, studying the features, using LSTM to provide its predictions of anxiety, and monitoring the situation.

VII. RESULTS

The evaluation of the AVRET system was conducted with respect to the parameters of anxiety prediction accuracy, adaptability, emotional responsiveness, deep learning convergence, personalization, and reliability. The research results conducted with the use of multimodal sensing and deep learning show that the reliability and adaptability level achieved is much higher than that typical of static VR therapy.

A. Anxiety Prediction Accuracy

The LSTM model has generated good predictions for anxiety from the different intensity sessions in VR, utilizing temporal-sequence processing, multimodal integration, continuous context, and its capability to adapt to emotional patterns. Table I summarizes the classification performance.

TABLE I. EVALUATION METRICS

Metric	Performance
Accuracy	90.0%
Precision	94.8%
Recall	94.1%
F1-Score	94.4%
Latency	0.8 sec

B. Training Performance

Training accuracy and loss trends (Fig. 3–4) suggest a regular pattern of convergence since accuracy improved steadily again and loss decreased – thus, the LSTM learned the patterns of stress development, fluctuation, escalation, and recovery processes without overfitting.

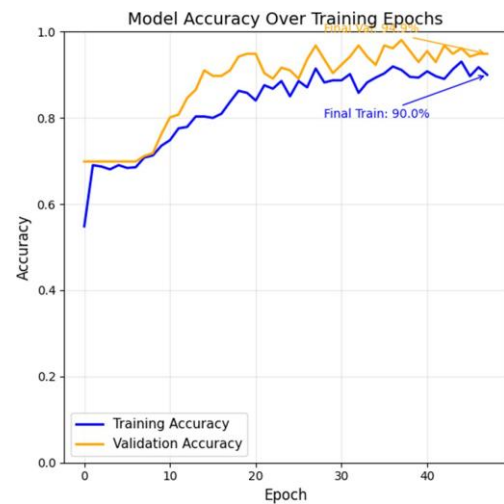


Fig. 3. Training accuracy curve of the proposed LSTM model.

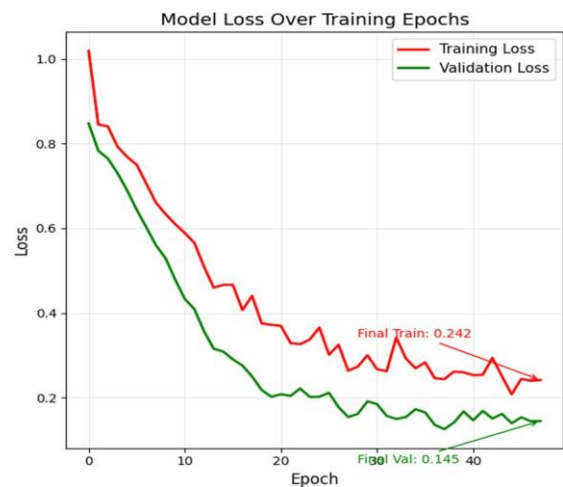


Fig. 4. Training loss curve of the proposed LSTM model.

C. Confusion Matrix Evaluation

Confusion-matrix analysis (Fig. 5–6) shows strong detection consistency with Low, Medium, and High anxiety classes with minimal misclassification, confirming the system's sensitivity to stress and emotional discomfort during VR immersion [13].

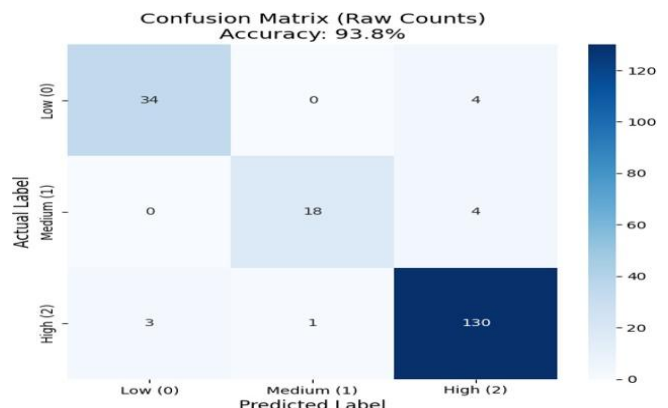


Fig. 5. Confusion matrix for anxiety classification.

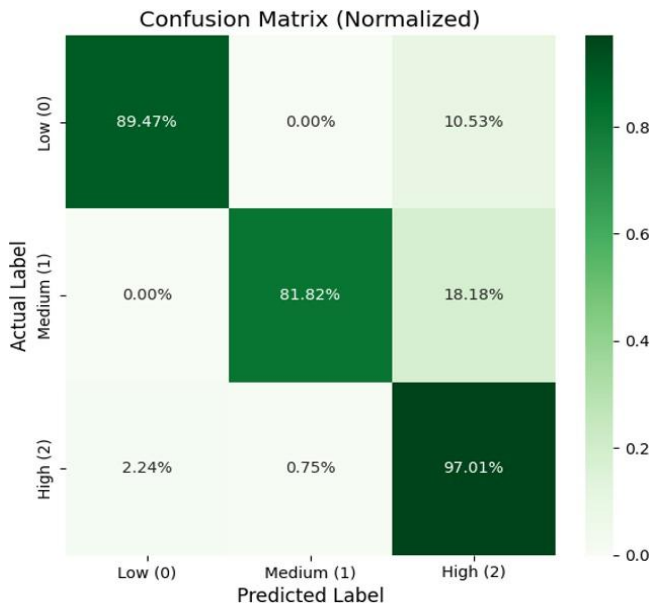


Fig. 6. Normalized confusion matrix for anxiety classification.

D. Multimodal Fusion Performance

Fusing HR, HRV, GSR, eye-tracking, and motion features substantially outperformed single-modality prediction (Table II), confirming that multimodal fusion enhances robustness and classification reliability.

TABLE II. COMPARISON OF PREDICTION APPROACHES

Method	Accuracy
Heart Rate Only	78.4%
GSR Only	80.1%
Eye Tracking Only	76.9%
Multimodal Fusion	95.2%

E. Adaptive VR and Physiological Signal Analysis

The adaptive controller successfully modulated scene complexity, exposure difficulty, sound intensity, object movement, crowd density, and environmental stimulation based on predicted anxiety [15]. Continuous multimodal monitoring (Fig. 7) shows HR rising, HRV declining, and GSR, pupil dilation, and eye blink rate varying under high-stress scenarios such as crowds, public speaking, and height exposure, showing that multimodal fusion achieves more reliable emotional representation than any single modality.

F. Adaptive VR Exposure Analysis

TABLE III. CLASSIFICATION REPORT FOR ANXIETY PREDICTION

Class	Precision	Recall	F1	Supp.
Low	91.9%	89.5%	90.7%	38
Medium	94.7%	81.8%	87.8%	22
High	94.2%	97.0%	95.6%	134

The controller continuously divided emotional state into Maintain, Reduce, or Increase Exposure based on the LSTM's predicted anxiety trajectory (Table III, Fig. 8), reducing

response as anxiety increased and increasing it as the user's emotional state improved, ensuring real-time responses, dynamic personalization, continuous stress regulation, and improved emotional safety.

Multimodal Physiological Signals During VR Exposure

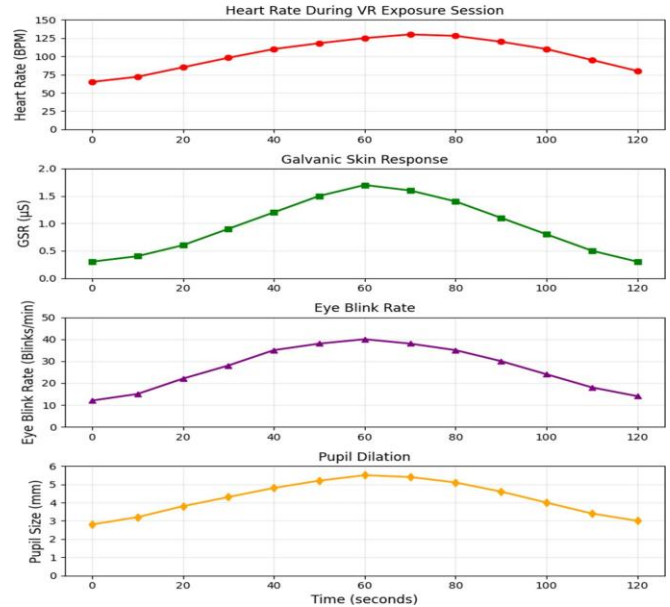


Fig. 7. Variation in multi-modal physiological signals during VR exposure.

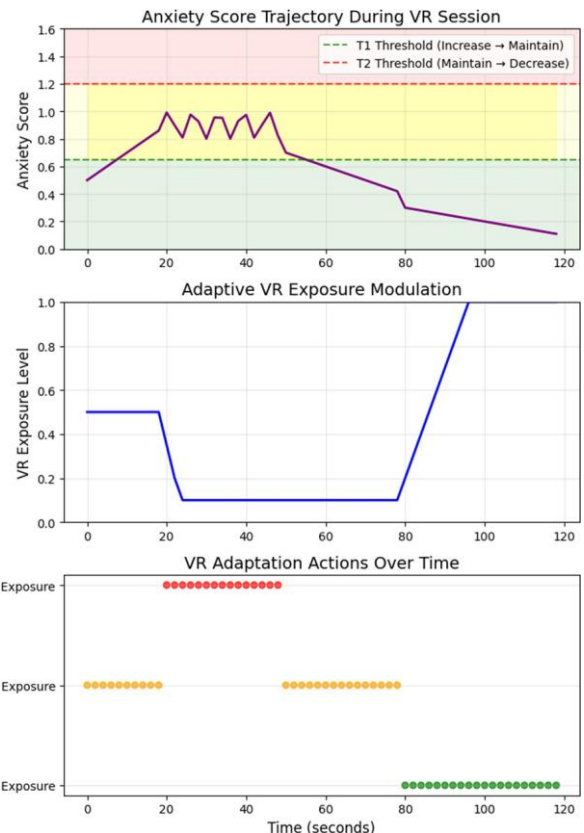


Fig. 8. Adaptive VR exposure modulation based on anxiety prediction.

G. Comparative Analysis

Table IV compares AVRET with existing approaches. Unlike traditional VRET (manual control, no adaptation) and single-modality predictors (HR-only, GSR-only, EEG-only, or eye-tracking-based models with partial or no adaptation), AVRET combines seven physiological/behavioral channels with an LSTM predictor and fully adaptive VR control, achieving markedly higher accuracy and confirming its advantage as an advanced, intelligent emotional-healthcare system.

TABLE IV. COMPARATIVE ANALYSIS

Method	Modalities	Model	RT Adapt.	VR Adapt.	Acc.
Traditional VRET	None	Manual	No	Static	Low
HR-Based	HR only	SVM	Partial	No	Moderate
GSR-Based	GSR only	RF	No	No	Moderate
EEG Emotion	EEG	CNN	Partial	No	High
Behavioral	Eye	RNN	Partial	Limited	Moderate
Proposed AVRET	Multimodal	LSTM	Yes	Full	Very High

VIII. DISCUSSION

These results support the effectiveness of multimodal physiological sensing, deep-learning-based anxiety prediction, and adaptive VR interaction for intelligent mental healthcare. This performance was driven by the LSTM architecture, which effectively learns temporal relationships among observations; unlike models that analyze each observation independently, it captured temporal dependencies in the design and resolution of anxiety, improving real-time prediction and adaptation. The adaptive VR controller used these predictions to continuously adjust exposure intensity, modifying environmental complexity, sound, and exposure duration to keep interactions emotionally balanced and avoid both overexposure and underexposure.

IX. CONCLUSION

This study proposed AVRET, a closed-loop intelligent healthcare system combining multimodal physiological sensing, behavioral analysis, LSTM-based deep learning, and adaptive VR control. The system collects HR, HRV, GSR, eye-tracking, blinking rate, pupil dilation, and other data continuously during VR therapy, processes it through a series of preprocessing, feature fusion, and deep-learning steps, and makes real-time predictions of anxiety. The experimental results demonstrate that AVRET is superior to static VR therapy in terms of prediction accuracy, emotional responsiveness, and adaptive personalization, with adaptive controller able to adjust exposure intensity based on changes in emotional state.

X. FUTURE SCOPE

This framework provides a foundation for future work to validate PA-VRET (EEG, EMG, facial expression) for richer emotional and cognitive-state recognition, and reinforcement learning or generative AI to automatically generate VR exposure environments based on patient progress. Future

directions include extending AVRET to post-traumatic stress disorder, depression, workplace stress, pediatric mental healthcare, and telehealth applications using emotionally responsive VR.

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