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Personalized Virtual Reality Exposure for MRI Preparation Using Adaptive Anxiety Prediction Models

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Abstract

Individual variability in anxiety response necessitates personalized preparation strategies prior to MRI. This study introduces an adaptive VR system that adjusts exposure intensity based on physiological and behavioral indicators. A machine learning model trained on 124 prior VR sessions predicted anxiety levels using heart rate, gaze fixation, and interaction latency. In a prospective study of 60 adult patients, VR exposure scenarios were dynamically modified to match predicted anxiety thresholds. Personalized VR exposure reduced STAI-state scores by 36.8%, compared with 21.5% in a non-adaptive VR control group ($p < 0.05$). Mean heart rate decreased by 9.4 bpm during exposure. Scan completion without interruption reached 98.3%. Adaptive personalization enhances VR-based MRI preparation efficacy by tailoring exposure intensity to patient-specific responses.

Keywords

Personalized virtual reality; MRI anxiety; adaptive exposure; physiological feedback; machine learning in healthcare

INTRODUCTION

Magnetic resonance imaging (MRI) is widely used in modern clinical practice because it provides high-resolution structural and functional information without ionizing radiation and plays an important role in diagnosis, treatment planning, and follow-up evaluation. Despite these advantages, the MRI environment itself remains a substantial source of distress for many adult patients. The narrow bore, loud gradient noise, restricted body position, and prolonged requirement to remain motionless can trigger anxiety, discomfort, claustrophobic reactions, and loss of perceived control during scanning. Recent evidence indicates that a considerable proportion of adults experience moderate or clinically meaningful anxiety before or during MRI, and that limited procedural explanation, unfamiliar surroundings, and time pressure in routine radiology workflows may further intensify anticipatory stress [1]. Clinical reports have also shown that claustrophobia and situational fear are among the most common reasons for disrupted examinations, often contributing to motion artifacts, repeated acquisitions, prolonged scan time, or premature

termination of the procedure [2]. These problems not only reduce image quality and diagnostic efficiency but also increase healthcare costs, interfere with scheduling, and place additional burden on both patients and imaging staff. Accordingly, there is a clear need for practical, scalable, and nonpharmacological preparation strategies that can improve patient tolerance while fitting within routine clinical workflows [3,4]. Virtual reality (VR) has emerged as a promising preparation tool because it allows patients to experience MRI-related sensory and procedural stimuli in advance within a controlled environment. By recreating key elements of the examination, including the tunnel structure, table movement, head or body coil placement, scanner sounds, and task instructions, VR can reduce uncertainty and help patients form more accurate expectations before the actual scan. Recent work has demonstrated that a dedicated VR-based MRI simulator implemented on standalone head-mounted devices can effectively prepare patients by reproducing both procedural steps and sensory conditions prior to scanning [5]. In pediatric imaging, randomized and feasibility studies have further demonstrated that VR-based MRI simulation can improve procedural success and reduce anxiety when compared with standard preparation materials [6,7]. Other game-based VR interventions have reported beneficial effects on emotional regulation and cooperation in awake MRI settings, supporting the clinical feasibility of immersive preparatory approaches [8]. Ongoing protocol-based studies are also evaluating smartphone-enabled or home-based VR exposure programs that can be completed before hospital visits, which may improve accessibility and reduce the burden on imaging departments [9]. Taken together, these findings suggest that VR has meaningful translational value as a preparatory tool for MRI, particularly because it can deliver repeatable, standardized, and sensory-rich rehearsal without requiring large physical mock-scanner installations. Even so, most currently available MRI-oriented VR systems rely on fixed or standardized content and do not adjust exposure intensity according to individual emotional responses. This is an important limitation because anxiety during MRI is highly variable across adults and is influenced by prior medical experience, trait anxiety, claustrophobic sensitivity, perceived coping ability, and expectations about the examination. A uniform VR scenario may therefore be insufficient for some users while unnecessarily intense for others. Evidence specific to adult populations remains relatively limited, and many existing systems still deliver identical training sequences regardless of individual stress tolerance or adaptation speed [10]. More recent developments, such as immersive entertainment devices designed to reduce claustrophobia during scanning, may improve subjective comfort, but they typically do not alter the exposure process in response to real-time emotional changes [11]. Systematic reviews from broader medical contexts support the general anxiety-reducing potential of VR, yet they also consistently note substantial heterogeneity in study design, intervention content, outcome measures, and sample size, which complicates interpretation and limits the strength of general conclusions [12,13]. These gaps indicate that the next stage of MRI preparation research should move beyond simple exposure delivery and toward systems that can account for patient-specific differences in stress response. At the same time, recent technological progress has made such personalization increasingly feasible. Physiological and behavioral signals can now be integrated into immersive systems to estimate emotional state during VR exposure with much greater precision than self-report alone. Measures such as heart rate, heart rate variability, and electrodermal activity have been used as indicators of autonomic arousal in immersive environments, while advances in sensing hardware have improved the practicality of collecting these signals in real time [14,15]. Machine learning models trained on multimodal data have shown promising performance in classifying or predicting anxiety levels during VR-based tasks, suggesting that dynamic emotional monitoring can be embedded into interactive systems [16,17]. Eye-tracking methods add another relevant dimension because gaze behavior can reflect attentional bias, environmental vigilance, avoidance patterns, and threat-related focus, all of which

are closely related to anxiety processing. Recent reviews have summarized reliable analytic frameworks and toolchains for gaze analysis in VR, highlighting their value for studying cognitive and affective responses under immersive exposure [18,19]. In addition, multisensor fusion approaches that combine physiological signals with gaze-related features have further strengthened the case for integrated affect estimation, as they may improve robustness compared with single-modality monitoring alone [20]. Together, these developments provide a strong technical foundation for adaptive VR systems that respond to patient-specific signals rather than relying on predetermined exposure pathways. However, important methodological and translational challenges remain before such systems can be adopted in MRI preparation practice. Many existing studies still rely on relatively small samples, short-term laboratory protocols, or narrowly defined user groups, which limits external validity and reduces confidence in generalizability across clinical settings [21]. Predictive models may also be sensitive to hardware configuration, signal noise, differences in environmental setup, and inter-individual variation in physiological baseline, all of which can reduce the stability of anxiety estimation in real-world deployment [22]. Systems based on a single data modality may be especially vulnerable to this problem because signal dropout, motion contamination, or device-specific artifacts can degrade performance. In addition, MRI preparation research has only rarely treated exposure intensity as an explicit, controllable variable that can be adjusted according to predicted anxiety thresholds. As a result, the field still lacks sufficient prospective evidence on whether real-time adaptation of immersive exposure can produce stronger reductions in state anxiety, better tolerance of scanner-related stress, and higher scan completion rates in adult patients compared with non-adaptive VR delivery [23,24]. Another unresolved issue is clinical usability: even technically sophisticated systems may have limited value if they are difficult to deploy, require extensive operator input, or cannot be integrated smoothly into radiology workflows. Therefore, research in this area must address not only emotional effectiveness, but also feasibility, interpretability, and operational practicality. Against this background, the present study develops a personalized VR exposure system for MRI preparation in adults, in which scenario intensity is dynamically modified according to predicted anxiety levels derived from physiological and behavioral indicators. A machine learning model is used to estimate anxiety during VR sessions, and the exposure parameters are adjusted to maintain stress within a tolerable range while preserving progressive familiarization with the MRI environment. Rather than treating all users as equally responsive to the same preparatory content, this study is designed around the premise that effective MRI preparation should be individualized, responsive, and clinically actionable. The main objective is to evaluate whether adaptive personalization can achieve greater anxiety reduction and better scan completion outcomes than a non-adaptive VR approach. The significance of this work lies in three aspects. It extends MRI preparation research from standardized immersive familiarization to closed-loop adaptive intervention. It links multimodal emotional monitoring with real-time exposure control in a radiology-relevant context. It also provides a practical framework for individualized anxiety management that may improve examination tolerance, reduce avoidable interruptions, and support more efficient MRI workflows in adult imaging settings. By focusing on both technical adaptation and clinical applicability, this study seeks to offer evidence that personalized VR preparation can serve not only as a supportive educational tool, but also as a meaningful strategy for improving the quality and consistency of MRI care.

2.Materials and Methods

2.1 Sample and Study Setting

The study was carried out in the MRI unit of a tertiary hospital from March to September 2025. Sixty adult patients scheduled for routine, non-emergency MRI examinations were enrolled. Eligibility criteria included age between 18 and 65 years, ability to understand study procedures,

and provision of written informed consent. Patients with diagnosed psychiatric disorders under active treatment, unstable cardiovascular conditions, severe visual impairment, or known intolerance to VR were excluded. Participants underwent MRI for neurological, musculoskeletal, or abdominal indications. Baseline data, including age, sex, prior MRI experience, and pre-exposure STAI-state scores, were collected. In addition, 124 previously recorded adult VR sessions obtained under comparable technical and environmental conditions were used to train the anxiety prediction model. These sessions followed the same simulation protocol and sensor configuration as the present study.

2.2 Experimental Design and Control Protocol

A randomized controlled design was applied. Participants were allocated to either an adaptive VR group (n = 30) or a non-adaptive VR group (n = 30) using a computer-generated randomization sequence. Both groups received a 15-minute MRI simulation delivered through the same VR hardware and baseline scenario structure. In the adaptive group, key exposure parameters, including scanner noise level, visual tunnel proximity, and motion cues, were adjusted in real time according to predicted anxiety scores derived from physiological and behavioral data. In the control group, exposure parameters remained constant throughout the session. Allocation concealment was maintained until intervention assignment. The protocol ensured identical exposure duration and scenario content across groups so that any observed differences could be attributed to adaptive intensity adjustment.

2.3 Measurement Procedures and Quality Control

Physiological signals were recorded continuously during VR exposure using a validated wearable monitoring device. Heart rate was sampled at 1 Hz. Signal noise was reduced using a 5-second moving-average filter. Eye-gaze fixation duration and saccade frequency were obtained through the integrated eye-tracking system of the VR headset. Interaction latency was defined as the time between a virtual prompt and the participant's response. State anxiety was assessed immediately before and after VR exposure using the State–Trait Anxiety Inventory (STAI-state). All devices were calibrated before each session. Room temperature and ambient sound were kept stable to reduce environmental variation. Data files were checked after each session. Records with more than 5% missing physiological data were excluded. Behavioral annotations were reviewed in a randomly selected 10% subsample, and inter-rater agreement exceeded 0.90.

2.4 Data Processing and Model Formulation

Physiological and behavioral variables were standardized using z-score normalization before model training. A multivariate linear regression model was used to estimate anxiety levels based on the archived dataset. The regression equation was defined as:

$$\widehat{A}=\beta_0+\beta_1 HR+\beta_2 GF+\beta_3 IL+\varepsilon$$

where $\widehat{A}$ represents the predicted anxiety score, HR is mean heart rate, GF denotes gaze fixation duration, IL refers to interaction latency, and ε is the error term. Model accuracy was evaluated using the coefficient of determination (R^2) and root mean square error (RMSE):

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(A_i-\widehat{A}_i)^2}$$

During real-time application, predicted anxiety values were compared with a predefined threshold based on the 75th percentile of baseline-adjusted scores. When the predicted value exceeded this threshold, exposure intensity was reduced stepwise within preset safety limits.

2.5 Statistical Analysis

Continuous variables are presented as mean ± standard deviation, and categorical variables are reported as counts and percentages. Normality was examined using the Shapiro–Wilk test. Between-group comparisons were performed using independent-sample t-tests for continuous outcomes and chi-square tests for categorical variables. Within-group changes in anxiety and heart rate were assessed using paired t-tests. Effect size was calculated using Cohen's d. Statistical significance was set at $p < 0.05$. All analyses were conducted using SPSS version 27.0 (IBM Corp., Armonk, NY, USA), and two-sided tests were applied.

3.Results and Discussion

3.1 Anxiety reduction and scan-related outcomes

Adaptive VR led to a greater decrease in MRI-related anxiety than the fixed-intensity VR condition. STAI-state scores declined by 36.8% in the adaptive group and by 21.5% in the non-adaptive group ($p < 0.05$). This difference indicates that adjusting exposure strength according to individual response can improve short-term emotional readiness. The uninterrupted scan completion rate reached 98.3%, showing that the reduction in anxiety was associated with better procedural tolerance. Previous MRI-preparation studies have reported that immersive familiarization reduces distress and improves cooperation; however, most protocols apply the same exposure sequence to all participants without intensity adjustment [25,26]. These findings suggest that personalization may strengthen the clinical effect of VR-based preparation.

3.2 Physiological regulation during exposure

Physiological data supported the psychological outcomes. Mean heart rate decreased by 9.4 bpm during VR exposure, indicating lower autonomic activation while the intervention was ongoing. This within-session decrease is relevant for MRI settings because discomfort and movement often arise when arousal increases during confined or noisy phases. The trend is consistent with research showing that physiological monitoring in VR environments can reflect stress levels and support adaptive control when paired with clear adjustment rules [27,28]. Fig.2 presents an example of a VR protocol that alternates scene intensity while tracking biosignals, illustrating how structured exposure combined with physiological monitoring can identify stress changes during immersion.

3.3 Effect of closed-loop intensity adjustment

The main distinction between groups was the use of closed-loop adjustment in the adaptive condition. Exposure content remained constant, but intensity was reduced when predicted anxiety approached a predefined individual threshold. This approach likely prevented sudden increases in distress while preserving meaningful exposure to MRI-related stimuli. Such calibration-based adjustment aligns with adaptive VR research that emphasizes the need to anchor decisions to each user's baseline rather than apply a universal cutoff [29]. Fig.1 illustrates a baseline calibration pipeline used in VR stress detection systems, which parallels the present strategy of individualized regulation during exposure.

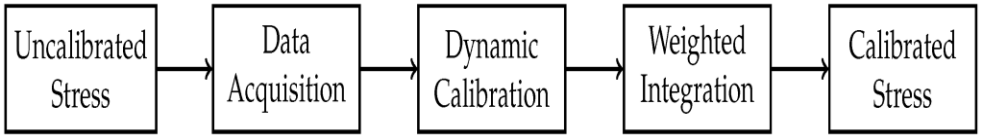


*Fig.1.**Adaptive baseline calibration workflow illustrating individualized stress threshold estimation and real-time exposure adjustment in a VR system.***

3.4 Comparison with existing approaches and limitations

Compared with routine preparation methods, such as verbal explanation or static media, adaptive VR combines realistic simulation with pacing control. Standardized VR programs improve familiarity but may not address rapid fluctuations in anxiety during exposure. The present findings suggest that real-time personalization can enhance both emotional and operational outcomes

within a single session. Nevertheless, several limitations should be considered. The sample size was moderate and drawn from one clinical center, which may limit generalizability. Model performance may vary under different hardware conditions, sensor configurations, or patient populations. Future research should include multi-center validation and examine robustness across device types and higher-risk subgroups.

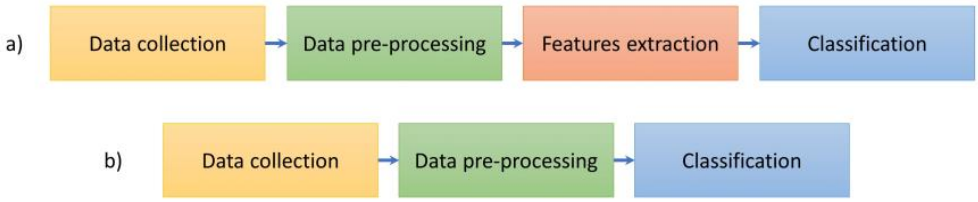


Fig.2.**VR experimental design with alternating low- and high-stimulus scenes for physiological signal recording and stress classification.**

4.Conclusion

The findings indicate that personalized VR exposure based on real-time anxiety prediction can effectively reduce MRI-related anxiety and improve scan tolerance in adult patients. By combining physiological and behavioral signals within a closed-loop control structure, exposure intensity was adjusted according to individual response patterns instead of being delivered at a constant level. The adaptive approach led to larger decreases in STAI-state scores, lower heart rate during exposure, and a high rate of scan completion without interruption compared with non-adaptive VR. These results support the clinical value of integrating multimodal monitoring with dynamic intensity control to address differences in patient anxiety responses. The proposed framework offers a practical method for individualized preparation in radiology and may be applicable to other medical procedures associated with situational anxiety. Several limitations should be noted. The study was conducted at a single center with a moderate sample size, and model performance may vary across different hardware systems or patient groups. Further multi-center validation and long-term follow-up studies are needed to confirm robustness and sustained benefit.

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