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# The effects of the generative adversarial network and personalized virtual reality platform in improving frailty among the elderly

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**As society ages, improving the health of the elderly through effective training programs has become a pressing issue. Virtual reality (VR) technology, with its immersive experience, is increasingly being utilized as a vital tool in rehabilitation training for the elderly. To further enhance training outcomes and improve health conditions among the elderly, this work proposes an integrated model that combines the Generative Adversarial Network (GAN), Variational Autoencoder (VAE), and Long Short-Term Memory (LSTM) network. The GAN generates realistic, personalized virtual environments, the VAE builds training models closely related to health data, and the LSTM network provides precise motion monitoring and feedback. They collectively improve training effectiveness and assist the elderly in enhancing their health. First, the work optimizes the GAN through alternating training of the generator and discriminator to create personalized virtual environments. Next, the VAE is trained by maximizing the marginal log-likelihood of observed and generated data, and the personalized training model is constructed. Finally, the optimized LSTM network is used to implement a motion monitoring and feedback system. Experimental evaluations reveal that the optimized GAN outperforms the non-optimized version in both image quality scores and diversity indices. The optimized VAE shows improvements in reconstruction error and personalized fitness scores, with a slight reduction in image generation time. Additionally, the training time for the VAE is reduced. After training, the elderly participants exhibit a significant increase in their daily step count and weekly exercise frequency, with p-values less than 0.01, indicating a substantial improvement in their physical activity. Assessments of psychological health show a notable decrease in anxiety and depression scores among the elderly participants.**

**Keywords** Deep learning, Virtual reality technology, Ba Duan Jin, Elderly exercise

## Research background and motivations

With the escalating global trend of aging populations, the proportion of elderly individuals is steadily increasing, posing a global challenge in terms of health care[1]. In the realm of elderly health management, particularly in the improvement of physical frailty, numerous challenges have long persisted[2]. Factors such as declining physical function, increasing chronic diseases, and reduced mobility often lead elderly individuals to experience issues like fatigue, muscle atrophy, and decreased balance[3,4]

In the methods of elderly health management, traditional exercises like the Ba Duan Jin, known for its simplicity, ease of learning, convenience, and effectiveness, have been widely utilized in elderly health care and rehabilitation training[5,6]. Originating from ancient China, Ba Duan Jin is a set of health-preserving exercises based on traditional Chinese medicine theories, designed to regulate qi and blood, and enhance physical strength and health through a series of body movements and breathing techniques[7]. However, with technological advancements and societal changes, traditional Ba Duan Jin training methods have revealed some shortcomings in practice, such as a lack of variety in training routines, inadequate supervision, and inconsistencies in movement standards[8]. These issues may lead to suboptimal training outcomes or limited health improvements in practice.

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This work not only focuses on addressing the problem of insufficient supervision but also enriches the training environment by introducing virtual reality (VR) technology to overcome the monotony of the training process. Additionally, it leverages deep learning techniques to provide standardized guidance for movements and address inconsistencies in execution. Comprehensively resolving these challenges can significantly enhance training effectiveness, enabling the elderly to benefit from more scientific and holistic training.

In addressing the challenges and issues in elderly health management, the rapid development of deep learning and VR technology offers new perspectives and methods. Deep learning, a machine learning approach based on neural networks, excels in data processing and feature extraction, demonstrating significant achievements in fields such as image recognition, natural language processing, and medical image analysis[9,10]. VR technology simulates real-world scenarios and environments, providing immersive experiences that offer richer, more intuitive training experiences and feedback mechanisms through virtual environments[11].

VR technology holds significant potential for applications in health management and rehabilitation training. Compared to traditional training methods, immersive VR environments can simulate real-world physical settings and enhance user engagement and training effectiveness through personalized customization. However, elderly users often face cognitive challenges and adaptation difficulties when using these technologies. To maximize training outcomes, it is crucial to provide a highly immersive and personalized virtual environment. Therefore, this work aims to explore how the application of VR technology can significantly improve the physical performance of the elderly and assist them in better adapting to and completing rehabilitation training.

## Research objectives

This work aims to use Generative Adversarial Network (GAN), deep learning techniques, and VR technology to help the elderly better practice Ba Duan Jin, thereby enhancing training effectiveness and improving health outcomes. It intends to explore the application of deep learning and VR technology in Ba Duan Jin training, evaluating their effectiveness in improving the physical frailty of elderly individuals, and providing a new and more effective solution for elderly health management. The research innovation lies in the integration of deep learning and VR technology. It utilizes the GAN to personalize virtual training environments, train models, and develop real-time monitoring and feedback systems for Ba Duan Jin training among the elderly. The literature review section comprehensively summarizes relevant studies and current practices in elderly health management. The research model details the combined application of deep learning and VR technology, including the principles and algorithms of the GAN, the design of personalized training models, and the construction of real-time monitoring and feedback systems. The experimental design and performance evaluation elucidate the experimental plans, environments, and parameter settings, and provide analysis and assessment of experimental results. This validates the effectiveness of deep learning and VR technology in improving the physical frailty of elderly individuals through Ba Duan Jin training. The conclusion section summarizes the work, proposes future research prospects and directions, and provides reference and guidance for innovation and practice in elderly health management. The core question of this work is how to optimize the personalization of VR environments by comparing different machine learning techniques. The research goal is to assess the performance of these techniques in improving the quality of virtual training environment generation, adaptability, and accuracy of user feedback, thereby providing more effective personalized health management solutions for the elderly.

To visually illustrate the interactions among the GAN, Variational Autoencoder (VAE), and Long Short-Term Memory (LSTM) models, a schematic diagram (Fig. 1) is provided. Specifically, the GAN generates personalized virtual environments, taking random noise and health data as input and producing high-quality virtual scenes as output. The VAE leverages health data to construct a personalized training model, and uses elderly individuals' health metrics and personal characteristics as input to output optimized training parameters. The LSTM model

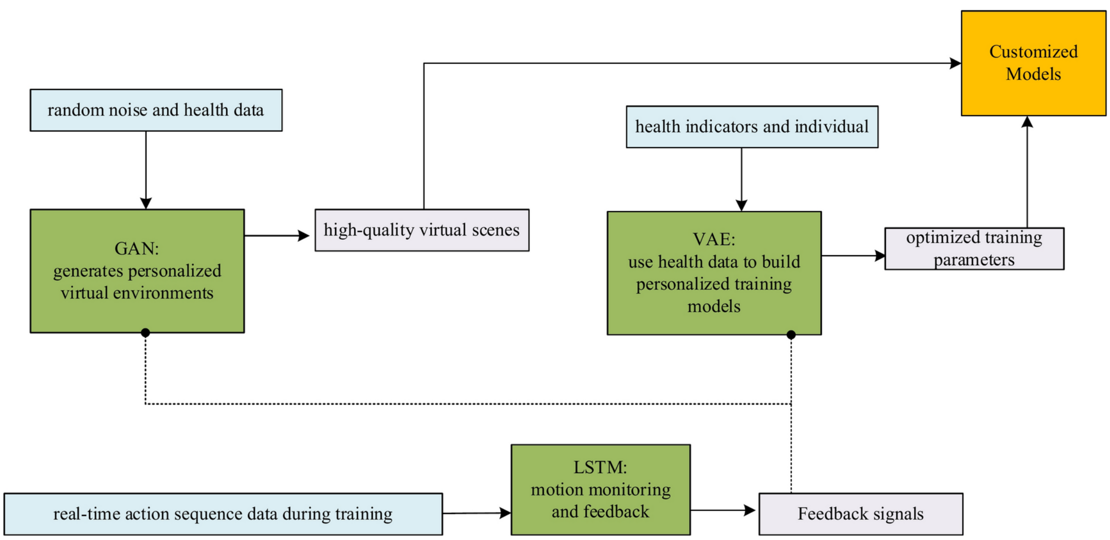


**Fig. 1**. Interaction Among GAN, VAE, and LSTM Models.

monitors the sequence of actions during training and provides feedback signals to optimize training movements in real time. Through the collaborative operation of these models, personalized optimization of the virtual training environment and real-time feedback are achieved.

This work designs and conducts a user experiment involving 190 elderly participants. These participants are divided into optimized and non-optimized virtual environment groups. The experimental results show that the optimized virtual environment significantly outperforms the non-optimized environment in terms of image quality, diversity, and personalized adaptability. Participants in the optimized environment increase their average daily step count by 40% and experience a 25% reduction in anxiety scores, demonstrating the effectiveness of the proposed approach in enhancing training outcomes and mental health. These findings validate the potential of the collaborative use of GAN, VAE, and LSTM models in improving frailty among the elderly.

## Literature review

In the field of elderly health management, researchers have conducted extensive studies to address the challenges and issues posed by aging societies[12]. An aging society refers to the social phenomenon in which the proportion of elderly individuals in the overall population gradually increases due to declining birth rates and longer life expectancy. This trend has led to a significant rise in health management and caregiving needs, particularly in improving the quality of life for the elderly, delaying aging, and preventing age-related diseases. Consequently, studying ways to improve the frailty conditions of the elderly is of great importance. These studies cover various aspects including health assessments, rehabilitation programs, and effectiveness evaluations of fitness activities for the elderly[13,14]. For instance, a comprehensive assessment of elderly health was conducted and prevalent issues were found, such as decreased sleep quality, osteoporosis, and cardiovascular diseases[15]. Similarly, long-term follow-up studies were conducted and it was discovered that regular moderate exercise helped maintain physical function and improve the quality of life among the elderly[16]. These findings highlight the multifaceted challenges in elderly health management, necessitating comprehensive solutions to improve their health conditions.

Over the past few years, Ba Duan Jin, as a traditional fitness method, has garnered widespread attention and application in the field of elderly health management[17,18]. Many researchers have explored the impact of Ba Duan Jin on the physical health of elderly individuals and proposed viewpoints regarding its effects and mechanisms[19,20]. For example, scholars conducted a 12-week follow-up study on a group of elderly individuals undergoing Ba Duan Jin training and found significant improvements in muscle strength, flexibility, and balance[21]. Similarly, researchers demonstrated that elderly individuals participating in Ba Duan Jin training showed significant improvements in psychological health, sleep quality, and life satisfaction[22].

Some researchers have started integrating deep learning algorithms and VR technology into Ba Duan Jin training to enhance training effectiveness and user experience. In recent years, deep learning technology has been widely applied in health management[23,24]. For instance, researchers utilized deep learning algorithms for real-time monitoring and recognition of elderly individuals' exercise behaviors, providing personalized exercise guidance and supervision[25].

Additionally, VR technology has been applied to health management for the elderly. Some studies explored the use of VR in rehabilitation training for older adults. scholars developed a VR-based rehabilitation system that simulated common home environments for the elderly, aiding in gait and balance training. The results indicated that elderly participants using the system showed significant improvements in balance and gait stability[26]. Moreover, VR technology can provide visual feedback through virtual environments, helping the elderly better understand and correct their movements, thereby significantly enhancing training outcomes. Further research has validated the potential of VR technology in elderly health management. For example, some scholars studied a VR-based cognitive training system designed to improve cognitive functions in the elderly by simulating complex daily tasks. They found that elderly participants using the system showed significant improvements in memory, attention, and problem-solving abilities, with the effects sustained even six months post-training[27]. Additionally, the application of VR technology in psychological health interventions for the elderly was investigated. A VR therapy was developed to help alleviate anxiety and depression among older adults. The results showed that, compared to traditional therapies, VR therapy was more effective in the short term, with a higher acceptance rate among elderly participants[28]. Finally, the use of VR in social interactions among the elderly was explored, particularly in cases of severe social isolation. The findings demonstrated that VR technology could provide immersive social experiences, helping the elderly stay connected with family and friends, thereby significantly improving their life satisfaction and mental health[29].

However, existing elderly health management solutions often have limitations and shortcomings[30]. Traditional rehabilitation training and fitness activities often lack personalization and specificity[31], failing to meet the diverse health needs of elderly individuals.

## Research model

### Joint application of deep learning and vr technology

Personalization is crucial for enhancing the effectiveness of elderly health management[32]. Due to the diverse physiological characteristics and health conditions of the elderly, traditional generalized health management approaches often struggle to meet their personalized needs[33]. Therefore, leveraging deep learning algorithms combined with VR technology is of significant importance in providing personalized health management solutions for the elderly. By analyzing elderly health data such as physiological indicators and physical activity patterns through deep learning algorithms, precise assessment and analysis of their health conditions can be achieved[34]. VR technology, on the other hand, can generate personalized training scenarios and models tailored to individual characteristics and needs, thereby offering customized health management services for the elderly. Figure 2 illustrates the relationship between elderly health management, deep learning, and VR technology.

Internet of Things (IoT) sensors are adopted to collect real-time physiological indicators, movement data, and environmental data from the elderly and the data are transmitted to deep learning models for analysis. This integration of multiple technologies enables the system to dynamically adjust the virtual training environment, providing more precise, real-time personalized training guidance. For instance, the system can automatically adjust the intensity and content of the training in the VR environment based on the elderly's real-time heart rate, blood pressure, and other physiological indicators, ensuring the safety and effectiveness of the training.

The technical implementation framework of this work comprises the following key modules:

(1) IoT Sensor Data Collection Module: IoT sensors deployed in the living environments of elderly participants collect real-time physiological indicators (such as heart rate and blood pressure), activity data, and environmental information (such as temperature and humidity). These data are transmitted via a wireless network to the data processing module.

(2) Data Processing and Deep Learning Analysis Module: The collected data undergo preprocessing (such as missing value imputation and data normalization) before being input into deep learning models (LSTM, GAN, VAE) for analysis. Specifically, the LSTM model analyzes time-series data to identify trends in health status changes. The GAN model generates realistic virtual training scenarios tailored to the user's health needs. VAE model constructs personalized training parameters, enabling customized training plans.

(3) Virtual Reality Environment Generation Module: Based on the outputs of the deep learning models, the system dynamically generates a VR training environment. For instance, the intensity and content of training scenarios are adjusted in real time according to the user's heart rate and activity level, ensuring both safety and effectiveness. The virtual environments generated by the GAN model exhibit the following features: Personalization: Scene backgrounds (such as a serene grassland for relaxation training) adapt to the user's health data (like heart rate and blood pressure). Dynamic Adaptation: Environmental elements (like weather and brightness) are adjusted in real time based on user performance, enhancing immersion. Enhanced Interactivity: Interactive objects (such as virtual coaches) are added to increase user engagement and participation. These VR environments indirectly enhance training outcomes and health improvements by boosting user engagement and interest.

(4) User Interaction and Feedback Module: Through VR devices, users interact with the virtual training environment. For example, users provide feedback on their training status via gestures or voice commands, and the system responds in real time with personalized training guidance. The system also monitors training data to adjust subsequent training sessions accordingly. In the user study, 200 elderly participants engage in VR-based Ba Duan Jin training, with 190 participants completing the study. Each participant practices Ba Duan Jin in the VR environment for 30 min daily over six weeks. During training, the VR environment automatically adjusts the intensity and pace based on real-time physiological indicators (like heart rate and blood pressure) and motion feedback, ensuring safety and personalization. At the end of each week, participants complete a 20-item questionnaire covering the following aspects: System Usability: such as ease of operation. Sense of immersion (such as whether the realism of the scene is perceived). Training effectiveness (such as whether action feedback helps improve training efficiency). Potential side effects (such as motion sickness symptoms, including nausea, and dizziness). To evaluate the impact of the training experience on mental health, the questionnaire

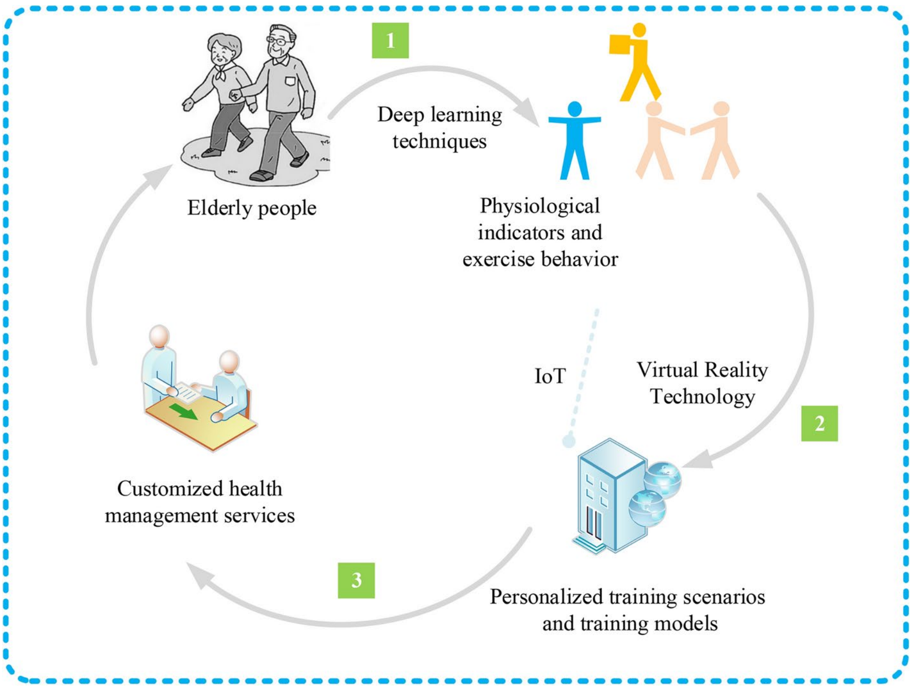


**Fig. 2**. Relationship among Elderly Health Management, Deep Learning, IoT, and VR Technology.

also includes subjective satisfaction scores on a Likert scale (1–10). According to the survey results (Table 1), the average satisfaction score is 8.5 (out of 10), with 87% of participants reporting significant improvements in their physical and mental health.

Specifically, in the VR environment, users interact with the virtual scene by wearing a Head-Mounted Display and motion capture devices (such as depth cameras or wearable sensors). These interactions include: Action Guidance: Users can perform Ba Duan Jin training movements under the guidance of a virtual coach. The virtual coach helps users accurately master each movement through clear step-by-step animations or real-time demonstrations. Real-Time Feedback: When the system detects inaccurate movements using an LSTM model, the virtual assistant immediately provides voice prompts (such as "Please lower your arms") or visual cues (such as color changes in the movement trajectory) to guide the user. Environmental Adaptation: The system adjusts environmental parameters in real-time based on the virtual scene generated by the GAN. For instance, if the user's physiological indicators (such as heart rate and blood pressure) show a high stress level, the environmental background may switch to a more calming natural scene (such as a forest or beach) to reduce the user's psychological burden. Emotional Monitoring and Interaction: The system uses natural language processing and facial expression analysis to detect the user's emotional state (such as anxiety and joy) and provides appropriate encouraging dialogue or adjusts the training content. For example, when the user is feeling down, the virtual assistant may use motivating language such as, "Great job! Keep it up!" Multidimensional Interaction: Users can not only complete training through body movements but also use gestures or voice commands to adjust the training content or virtual scene. For example, users can say "Next session" or wave to switch to the next movement. Dynamic Adjustment and Data Feedback: The system collaborates with VAE and GAN to dynamically optimize training intensity and the virtual scene. For example, the accuracy of the user's movements is fed back in real-time to the VAE to adjust the next training parameters; simultaneously, the GAN generates virtual training scenes that better align with the user's state, providing a personalized experience.

These modules form a dynamic closed-loop personalized health management system through high integration and mutual collaboration. The specific data flow relationships are as follows: Data collected by IoT sensors is transmitted to deep learning models for processing, and the generated analysis results are directly used to adjust the VR environment and training content. User feedback further optimizes the model's parameters and strategies, continuously improving the system's performance.

In the VR environment, these three models work collaboratively to provide a personalized interactive experience: GAN: Responsible for generating virtual scenes that match the user's current state. For example, during training, the GAN generates different scene backgrounds (such as relaxation, focused training, or dynamic changing scenes) based on the user's physiological feedback. VAE: Responsible for optimizing training parameters and dynamically adjusting the difficulty of training movements based on the user's health data (such as heart rate and blood pressure). For example, the VAE determines whether the next movement requires increasing repetitions or reducing intensity based on the user's performance. LSTM: Monitors the user's movement sequences in real time and provides feedback. For example, when inaccurate movements are detected, the LSTM triggers the virtual assistant to issue correction prompts and sends feedback signals to the GAN and VAE to optimize the environment and training parameters.

## Design of the model for improving elderly frailty based on GAN

*Virtual environment design based on adaptive GAN*

This paper proposes an adaptive GAN approach, where the network introduces an adaptive mechanism to dynamically adjust the parameters of the generator and discriminator based on real-time feedback and health data from the elderly. This allows the generated virtual environment to better align with the elderly's health status and personalized needs. GAN consists of two parts: the Generator and the Discriminator, aimed at learning to generate virtual environments similar to real samples[35]. Figure 3 illustrates the structure of GAN.

First, this work defines the input to the generator $G$ as a random noise vector $z$ and the elderly's health data $D$. The output is the image of the virtual environment, denoted as $X_{\text{fake}}$, as shown in Eq. (1). The objective of the generator is to generate virtual images that closely resemble real environment images, thereby making it difficult for the discriminator to distinguish between real images $X_{\text{real}}$ and fake images $X_{\text{fake}}$.

$$X_{\text{fake}} = G(z) \tag{1}$$

Next, the discriminator $D$ is defined with its input as an image $X$ and its output as a probability value, indicating the likelihood that the input image is a real image. The discriminator's objective is to distinguish between real images and fake images by maximizing the probability of correctly identifying real images and minimizing the probability of incorrectly identifying fake images. This is formulated as shown in Eqs. (2):

| Evaluation Metric | Average Score | Standard Deviation (SD) | Satisfaction Rate (≥ 8 points) |
|---|---|---|---|
| Ease of Operation | 8.7 | 1.1 | 85% |
| Sense of Immersion | 8.9 | 1.0 | 89% |
| Training Effectiveness | 8.5 | 1.2 | 87% |
| Overall Satisfaction | 8.5 | 1.2 | 87% |

**Table 1**. Subjective Satisfaction Scores.

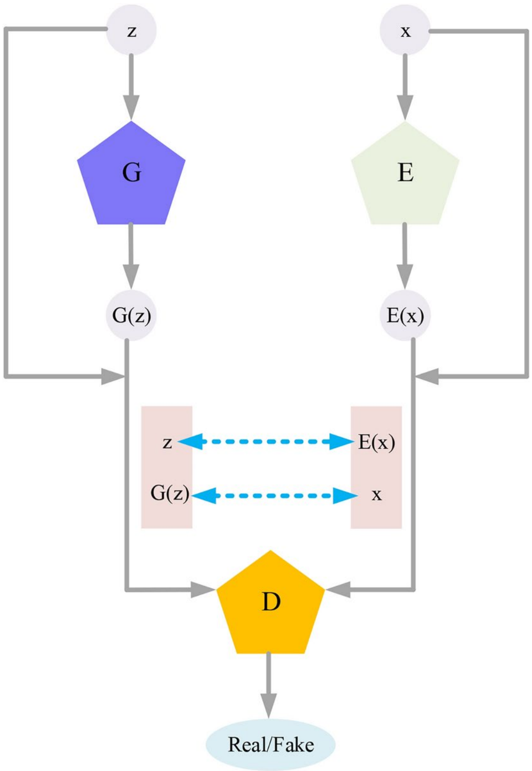


**Fig. 3**. The Structure of GAN.

$$D\left(X\right)\to\left\{\begin{array}{l}1, if\ X\ is\ real\ image\\0, if\ X\ is\ fake\ image\end{array}\right. \tag{2}$$

Due to the stability issues in training GAN, this work proposes an enhanced training strategy. The GAN is optimized by alternating the training of the generator and the discriminator[36,37]. Mini-batch Feature Matching (MBFM) is employed to improve the stability of GAN training[38]. This approach aims to alleviate mode collapse and mode oscillation during training by introducing a feature matching loss between the generator and discriminator[39].

In order to implement this, a pre-trained convolutional neural network (CNN) is utilized to extract features from both real and fake images. The difference in these features is computed and incorporated into the generator's objective function as the feature matching loss, defined as follows in Eq. (3):

$$L_{\mathrm{MBFM}}=\frac{1}{N}\sum_{i=1}^{N}\left\|\mathcal{F}\left(x_i\right)-\mathcal{F}\left(G\left(z_i\right)\right)\right\|_2^2 \tag{3}$$

$N$ is the batch size, $x_i$ represents real images, $z_i$ denotes noise vectors, and $\mathcal{F}$ is a convolutional neural network used for extracting image features. Minimizing the MBFM loss promotes the generator to produce virtual images closer to real images, thereby improving the training stability of the GAN.

The objective function for the adaptive mechanism is given by Eq. (4):

$$\mathcal{L}_{\mathrm{Adaptive}}=\mathbb{E}_{X_{\mathrm{real}}\sim p_{\mathrm{data}}(X)}\left[\log D\left(X_{\mathrm{real}}\right)\right]+\mathbb{E}_{z\sim p_z(z)}[\log(1-D(G(z,D)))] \tag{4}$$

During the training process, the parameters of the generator $G$ and discriminator $D$ are adaptively adjusted based on real-time feedback from the elderly, as shown in Eq. (5):

$$\theta_G\leftarrow\theta_G-\eta\nabla_{\theta_G}\mathcal{L}_{\mathrm{Adaptive}},\theta_D\leftarrow\theta_D+\eta\nabla_{\theta_D}\mathcal{L}_{\mathrm{Adaptive}} \tag{5}$$

$\eta$ represents the learning rate. Through this adaptive adjustment mechanism, the GAN can generate virtual environments that better align with the actual needs and health status of the elderly, thereby enhancing the personalization and effectiveness of the virtual training.

To assess the effectiveness of GAN in virtual environment generation, this work defines the following three core evaluation metrics: Image Quality Score (IQS): Rated by three domain experts based on a Likert scale (1–10 points) for the realism and visual quality of the generated images, with the average score used as the final result. Diversity Index (DI): Evaluates the diversity of the generated images by calculating the range of pixel distributions (such as color and texture). A higher value indicates richer generated content. Generation Time: Measures the time required to generate a virtual scene image (unit: seconds per image) to assess the efficiency of the generator. These metrics are selected based on the objectives of GAN: to generate realistic, diverse, and efficient virtual scene images.

*Construction of personalized training model*
A personalized training model is constructed using the VAE to support the improvement of frailty conditions in elderly individuals. Unlike GAN, VAE can learn latent representations of data, enabling more precise construction of personalized models[40].

First, health data of elderly individuals practicing Ba Duan Jin exercise, including physiological indicators and exercise behaviors, are collected as inputs to the encoder. Additionally, individual characteristics and preferences are considered as auxiliary inputs to the encoder, enhancing the customization of the personalized training model[41,42]. The objective of the encoder is to output distribution parameters in the latent space: $q_{\phi}(z \mid x)$. $x$ represents the input health data and individual characteristics, $z$ denotes the latent variable, and ϕ represents the parameters of the encoder.

A decoder is designed to map the latent variable back to the original data space, generating training model parameters θ that match the individual characteristics and health data of elderly individuals: $p_{\theta}(x \mid z)$.

Training the VAE involves maximizing the marginal log-likelihood of observed and generated data, and introducing the Kullback–Leibler (KL) divergence, as shown in Eq. (6):

$$\mathcal{L} = -\mathbb{E}_{q_{\phi}(z|x)}\left[\log p_{\theta}(x \mid z)\right] + D_{KL}\left[q_{\phi}(z \mid x) \parallel p(z)\right] \tag{6}$$

$D_{KL}$ represents the KL divergence and $p(z)$ denotes the prior distribution of latent variables.

By introducing the KL divergence regularization term, the distribution of the latent space is constrained to approximate the prior distribution. This enhances the training effectiveness and personalization of the model. Ultimately, based on the health data and individual characteristics of elderly individuals, a customized training model is generated to support the improvement of their physical condition.

Here, the primary purpose of the VAE is to extract latent variables from the health data and individual characteristics of elderly individuals to generate more precise personalized training parameters. The VAE takes the elderly person's health data (like heart rate, blood pressure, and body fat percentage) and individual characteristics (like age, gender, and health history) as inputs, and the encoder extracts their latent representations (latent variables z). The decoder then maps these latent variables back to specific parameters for the training model (such as the difficulty and pace of training movements). For instance, for elderly individuals with weaker cardiopulmonary function, the system will automatically reduce the intensity of movements or slow the pace, thereby reducing exercise stress and improving training safety.

The generated artificial health data primarily serve to enhance the robustness and generalization ability of the training model. By generating various virtual data simulating different health conditions (such as heart rate fluctuations at different health levels), the VAE can expand the training dataset, making the model more adaptable when processing real elderly data. This method significantly improves model performance, particularly in scenarios with scarce data.

The personalized training parameters generated by the VAE are input into the LSTM model, serving as reference benchmarks for movement monitoring and feedback. Based on this, reinforcement learning algorithms further optimize these parameters according to the user's real-time training feedback signals (such as movement accuracy and fatigue state). For example, when the user reports that a training movement is too difficult, the system will dynamically adjust the parameters based on immediate reward signals, ensuring the training intensity remains moderate.

*Integration of reinforcement learning and social psychological factors in the motion monitoring and feedback system*
This work proposes an action monitoring and feedback system based on the LSTM network, utilizing VR technology to real-time monitor and guide the training action sequences of elderly individuals.

First, the structure of LSTM is defined. LSTM takes as input the sequence data of elderly individuals' movement poses. It undergoes feature extraction and memory processing through multiple LSTM units, culminating in the output of action feedback guidance via a fully connected layer[43,44]. Figure 4 illustrates the specific structure.

The goal of LSTM is to learn the complex relationship between motion pose sequences and feedback guidance to accurately generate feedback guidance.

Additionally, a discriminator is designed to evaluate the effectiveness of the generated feedback guidance. The discriminator takes as input the motion pose sequence data of elderly individuals and the generated feedback guidance. After passing through fully connected layers, the discriminator outputs a probability value indicating whether the input feedback guidance is effective[45]. The discriminator's output $(y_t, \widehat{y_t})$ is formulated as shown in Eq. (7):

$$D\left(y_t, \widehat{y_t}\right) = \mathrm{Sigmoid}\left(\mathrm{FC}\left(y_t, \widehat{y_t}\right)\right) \tag{7}$$

$y_t$ represents the generated feedback guidance, $\widehat{y_t}$ denotes the true feedback guidance, and FC denotes the Fully Connected Layer.

To further optimize the LSTM model, this work introduces reinforcement learning algorithms. A reward mechanism is incorporated during the training process. This enables the system to dynamically adjust the parameter settings of the LSTM model based on feedback signals from the elderly's training results (such as

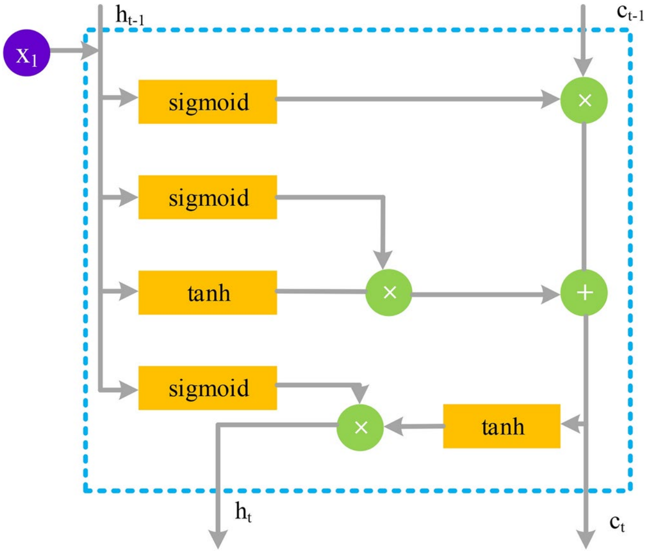


**Fig. 4**. The Structure of LSTM.

movement accuracy and posture coordination). Specifically, the objective function of the reinforcement learning can be expressed as Eq. (8):

$$R\left(s_t, a_t\right) = \sum_{t=1}^{T} \gamma^{t-1} r_t \tag{8}$$

In this context, $R\left(s_t, a_t\right)$ represents the total reward obtained by taking action $a_t$ in state $s_t$, $\gamma$ is the discount factor, and $r_t$ is the immediate reward received at time step *t*. By maximizing the cumulative reward, the system can generate training guidance that better aligns with the personalized needs of elderly individuals.

To comprehensively evaluate the effectiveness of the action monitoring and feedback system, this work proposes the following core evaluation metrics. Action Recognition Accuracy (ARA): it is the classification accuracy of the system in recognizing real-time user movement actions (unit: %), used to assess the LSTM's ability to recognize action features. Feedback Response Time (FRT): it is the time delay between the user completing an action and the system generating feedback (unit: seconds), used to evaluate the real-time responsiveness of the system. User Satisfaction Score (USS): based on a questionnaire survey, users rate their system experience using a Likert scale (1–10 points), with the average score serving as the satisfaction metric. These metrics are designed based on the objectives of the LSTM model and evaluate the performance of the action monitoring and feedback system from three dimensions: accuracy, real-time responsiveness, and user experience. In the experimental design, three independent evaluators use a standardized Likert scale to assess image quality and user satisfaction, minimizing subjective bias in scoring. The DI is calculated by determining the SD of different pixel distributions in the generated images. ARA and FRT are automatically calculated through system log records and quantitative analysis tools.

In addition to considering the physical health of the elderly, this work also incorporates social and psychological factors through natural language processing technology. The system analyzes the language and behavioral data of elderly individuals to assess their emotional states (such as anxiety and loneliness) and uses these emotional indicators as inputs to influence the settings and feedback of the virtual training environment. For example, if the system detects that an elderly person is feeling down, it may adjust the training content or provide more encouraging feedback to enhance their engagement and training outcomes.

By alternately training LSTM and the discriminator, it is possible to progressively optimize LSTM to generate more effective feedback guidance. Specifically, introducing an attention mechanism enhances the model's focus on different time steps within the input sequence[46], as shown in Eqs. (9)-(11):

$$\alpha_t = \mathrm{Softmax}\left(v^T \tanh\left(W_h h_t + W_y y_{t-1} + b\right)\right) \tag{9}$$

$$c = \sum_t \alpha_t h_t \tag{10}$$

$$y_t = \mathrm{FC}(c) \tag{11}$$

$\alpha_t$ represents the attention weight at time step *t*, *c* is the weighted context vector, and *v* denotes the weight vector for attention weights, used in calculating the attention weights. $W$ denotes the weight matrix, and *b* denotes the bias term. *h* represents state information. $y_t$ denotes the output at time *t*.

The quantification equation for health improvement is as follows:

$$H_{improve} = \frac{1}{T}\sum_{t=1}^{T}\left(R_{acc}(t) + R_{form}(t) + R_{eff}(t)\right) \tag{12}$$

$H_{improve}$ is the total quantified indicator of health improvement for the user after training. $T$ represents the total number of time steps in the training process. $R_{acc}(t)$ is the reward signal for the action accuracy feedback at time step *t*. $R_{form}(t)$ is the reward for the standardization of the action posture at time step *t*. $R_{eff}(t)$ is the reward for the improvement in action efficiency at time step *t*.

The virtual environment adjustment rule is given by Eq. (13).

$$\theta_{adjust} = \lambda \cdot \left(\frac{1}{T}\sum_{t=1}^{T} R_{eff}(t)\right) + \mu \tag{13}$$

$\theta_{adjust}$ is the adjustment amount for the virtual environment parameters (such as training intensity and virtual background complexity). $\lambda$ and $\mu$ are weight parameters used to balance the contributions of action efficiency and background complexity.

## Experimental design and performance evaluation

### Experimental materials and experimental design

To conduct experiments aimed at improving the health conditions of elderly individuals, this work selects 200 elderly people aged 65 and above from a specific region. The sample size of 200 participants is determined based on a power analysis conducted prior to the research. The expected effect size is set at 0.5, with a power level of 0.8, ensuring that the sample size would be sufficient to detect significant differences at a 5% significance level. During the study, 10 participants are excluded due to non-compliance or withdrawal, resulting in a final sample size of 190 individuals. The required specific experimental materials are as follows:

1) Health Assessment Data: Physiological Indicators: Data on heart rate, and blood glucose levels. Exercise Behavior Data: Number of steps, and exercise frequency, including recording the number of times and duration of moderate to vigorous intensity exercise per week[47]. Body Composition Data: Body fat percentage and muscle mass. Psychological Health Status: Anxiety and depression scores evaluated monthly using the standard Symptom Check List (SCL)-90[48,49].

2) Ba Duan Jin Training Program: Training Videos and Teaching Materials: Each video lasts approximately 10–15 min, with a total training period of 30 days.

Stratified randomization is employed to control for potential confounding variables, including gender, previous VR experience, and baseline health status. Participants are matched based on these variables to ensure comparability between groups under different experimental conditions. All subjective health indicators (such as anxiety and depression scores) are standardized according to baseline measurements to account for individual differences prior to the intervention. This approach ensured that any observed changes reflected the effects of the intervention rather than baseline variability. Participants are randomly assigned to either the optimized or non-optimized virtual environment group, with the randomization process using computer-generated sequences to ensure fair group allocation.

Considering the participants' age and use of VR technology, the work closely monitors symptoms of simulator sickness, including nausea, disorientation, and eye strain. Participants are informed of these risks, and breaks are scheduled during VR sessions to mitigate these effects. Additionally, a pre-screening for VR sensitivity is conducted to minimize the occurrence of severe symptoms.

During the experiment, participants engage in a series of guided Ba Duan Jin exercises within the virtual environment, designed to simulate daily activities. The optimized VR environment includes personalized elements tailored to each participant's preferences and health status, such as adjusting the speed of the Ba Duan Jin exercises based on real-time feedback.

The work utilizes a within-subject experimental design, with each participant experiencing both the optimized and non-optimized virtual environments in a balanced order. Each session lasts 30 min, with a one-week interval between sessions to prevent carryover effects. The research is divided into three phases: baseline assessment, VR training, and post-training assessment.

### Performance evaluation

Before evaluating the model performance, descriptive statistical analysis is conducted on the research sample. The research involves 190 participants, with a mean age of 70.5 years (SD = 5.4). The gender distribution is 45% male and 55% female. Baseline health assessments are used to evaluate the participants' health status, revealing an average heart rate of 78 bpm (SD = 7.2) and an average blood glucose level of 108 mg/dL (SD = 15.3). The Shapiro–Wilk test is performed to assess the normality of the data, indicating that the physiological indicators are approximately normally distributed ($p > 0.05$).

*Model performance evaluation*

The performance of the generated models is evaluated through a series of quantitative metrics, primarily assessing virtual environment generation effectiveness, personalized training model accuracy, and the effectiveness of motion detection and feedback systems. In order to achieve this, multiple experiments are designed and various indicators are compared. Specifically, image quality ratings, personalized adaptability, and user satisfaction

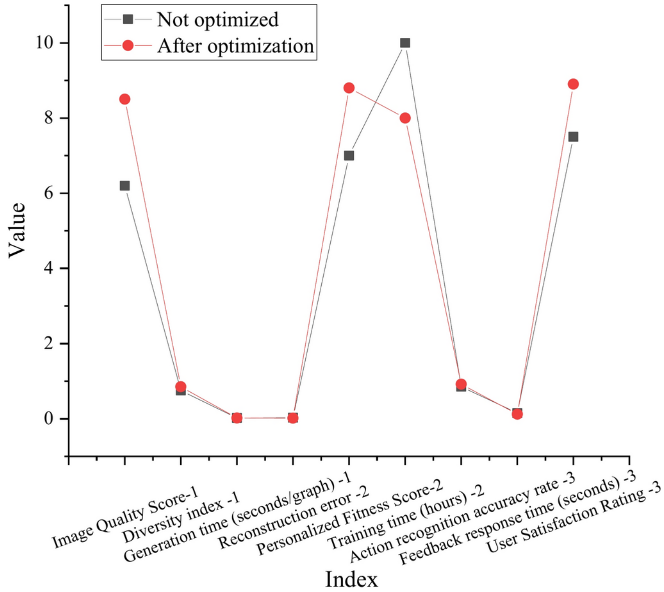


**Fig. 5**. Model Performance Evaluation.

| Indicator | Mean Before Optimization | Mean After Optimization | Difference | t-value | p-value | Significance |
|---|---|---|---|---|---|---|
| IQS | 6.2 | 8.5 | 2.3 | 5.32 | < 0.01 | Yes |
| DI | 0.75 | 0.85 | 0.1 | 3.45 | < 0.01 | Yes |
| Reconstruction Error | 0.025 | 0.015 | -0.01 | -4.25 | < 0.01 | Yes |
| Personalization Adaptability Score | 7 | 8.8 | 1.8 | 3.92 | < 0.01 | Yes |
| USS | 7.5 | 8.9 | 1.4 | 3.6 | < 0.01 | Yes |

**Table 2**. Significance Test Results for Model Performance Evaluation.

scores are evaluated by three experts invited by this work in the field, and the averages are obtained. Experts assess image quality, personalization adaptability, and user satisfaction using standardized scales, specifically a Likert scale for subjective ratings. The scores are averaged across three independent evaluators to minimize bias and ensure consistency in the ratings. In Fig. 5, 1 denotes virtual environment generation effectiveness, 2 denotes personalized training model, and 3 denotes motion detection and feedback system. Figure 4 illustrates the results.

Table 2 presents the significance test for model performance evaluation. The DI is calculated by measuring the distance between the feature distribution of generated images in the virtual environment and the feature distribution of real environment images, using the Fréchet Inception Distance (FID) method. A lower FID value indicates that the feature distribution of the generated images is closer to that of the real images, suggesting higher diversity.

Figure 5 and Table 2 suggest that the optimized GAN outperforms the unoptimized GAN in both IQSs and diversity indices. This indicates that optimizing hyperparameters by introducing feature matching loss significantly enhances the GAN's ability to produce realistic and diverse virtual environments. Additionally, Table 1 reveals a slight reduction in generation time following optimization, further improving efficiency. The optimized VAE also demonstrates improvements in reconstruction error and personalization adaptability scores.

In the ablation experiment, the GAN, VAE, and LSTM modules are removed individually to test their impact on key metrics. The ablation experiment validates the role of each module in the overall system. GAN significantly affects the image quality and diversity of the virtual environment, VAE optimizes the accuracy of the personalized training model, and LSTM plays a crucial role in the effectiveness of the action monitoring and feedback system. Table 3 shows the results of the ablation experiment.

The results in Table 3 show that after removing GAN, the image quality score of the virtual environment decreases by 18%, and the personalized adaptability score decreases by 12%. After removing VAE, the reconstruction error of the training model increases by 40%, and the personalized adaptability score decreases by 15%. After removing LSTM, the accuracy of the action feedback system decreases by 8%, and the USS drops by 10%. This indicates that GAN plays a crucial role in the image quality and diversity of the virtual environment, VAE is essential in building personalized models, and LSTM significantly impacts the accuracy of the action monitoring and feedback system.

| Module | IQS | DI | Reconstruction Error | Personalization Adaptability Score | ARA | USS |
|---|---|---|---|---|---|---|
| Full Model | 8.5 | 0.85 | 0.015 | 8.8 | 0.92 | 8.9 |
| Remove GAN | 6.9 (-18%) | 0.7 (-18%) | 0.018 | 7.7 (-12%) | 0.9 | 8.7 (-2%) |
| Remove VAE | 8.4 | 0.85 | 0.021 (+40%) | 7.5 (-15%) | 0.91 | 8.6 (-3%) |
| Remove LSTM | 8.5 | 0.85 | 0.015 | 8.8 | 0.85 (-8%) | 8.0 (-10%) |

**Table 3**. Ablation Experiment Results.

| Indicator | Mean Before Training | Mean After Training | Normality Test p-value | Test Selected | t-value | p-value | Significance |
|---|---|---|---|---|---|---|---|
| Heart Rate (bpm) | 80 | 75 | 0.15 | Paired t-test | -5 | < 0.01 | Yes |
| Blood Glucose (mg/dL) | 110 | 100 | 0.2 | Paired t-test | -4.32 | < 0.01 | Yes |
| Daily Steps | 5000 | 7000 | 0.1 | Wilcoxon Test | -3.25 | < 0.01 | Yes |
| Weekly Exercise Frequency (times) | 2 | 4 | 0.05 | Wilcoxon Test | -2.92 | < 0.01 | Yes |
| Body Fat Percentage (%) | 30 | 27 | 0.25 | Paired t-test | -3.5 | < 0.01 | Yes |
| Muscle Mass (kg) | 45 | 47 | 0.3 | Paired t-test | 2.1 | < 0.05 | Yes |
| Anxiety Score (points) | 40 | 30 | 0.03 | Wilcoxon Test | -3.4 | < 0.01 | Yes |
| Depression Score (points) | 35 | 25 | 0.04 | Wilcoxon Test | -3.5 | < 0.01 | Yes |

**Table 4**. Significance Test Results for Health Improvement Assessment in the Elderly.

| Indicator | Average Change (Traditional Group) | Average Change (Platform Group) | p-value | Significance |
|---|---|---|---|---|
| Heart Rate Decrease (bpm) | 3 | 5 | < 0.05 | Yes |
| Daily Steps Increase (%) | 20% | 40% | < 0.01 | Yes |
| Anxiety Score Decrease (%) | 15% | 25% | < 0.01 | Yes |
| Depression Score Decrease (%) | 18% | 28% | < 0.01 | Yes |

**Table 5**. Controlled Experiment Results.

*Evaluation of elderly health improvement*

In order to assess the effectiveness of the elderly health improvement model proposed, various quantitative metrics are employed for pre- and post-training comparisons. These metrics include physiological indicators, exercise behavior data, body composition data, and psychological health status. Changes before and after training are compared to evaluate the significance of training effects. Anxiety and depression scores are derived from the anxiety and depression subscales of the SCL-90 scale, using standardized scores (T-scores). Each subscale consists of 10 questions, with scores ranging from 0 to 50. Higher scores indicate higher levels of anxiety or depression. The changes in scores before and after training are subjected to significance analysis using paired t-tests. Table 4 provides an overview of the overall effect of the training on the improvement of elderly individuals' health.

Table 4 demonstrates that after training, there is a general decrease in heart rate and blood glucose levels among elderly individuals. The reduction in heart rate is particularly significant, with p-values less than 0.01, indicating a substantial improvement in cardiovascular health due to the training. Elderly participants also exhibit significant increases in daily average step counts and weekly exercise frequency post-training, both with p-values less than 0.01. It indicates a considerable enhancement in their physical activity levels. Moreover, post-training, there is a notable decrease in body fat percentage and an increase in muscle mass among the elderly, with body fat percentage decreasing by 10% and muscle mass increasing by 4.44%, both with p-values less than 0.05. This suggests that the training not only effectively reduces body fat but also increases muscle mass. Evaluation of psychological health status reveals significant decreases in anxiety and depression scores among elderly individuals, with anxiety scores decreasing by 25% and depression scores by 28.57%, both with p-values less than 0.05. These findings indicate that the training significantly improves the psychological well-being of the elderly.

To verify whether the health improvement is caused by the platform, a controlled experiment is designed to compare elderly individuals trained using traditional Ba Duan Jin video training with those trained using this platform. Table 5 displays the results.

Figure 5 shows that in the group trained using traditional video, heart rate decreases by 3 bpm, daily steps increase by 20%, and anxiety score decreases by 15%. In contrast, in the group trained using the platform, heart rate decreases by 5 bpm, daily steps increase by 40%, and anxiety score decreases by 25%. The data from both groups are validated through an independent sample t-test, showing significant differences ($p < 0.05$). This indicates that the platform developed significantly improves training effectiveness in terms of personalization and real-time feedback.

## Discussion

The core of this work lies in the integration of GAN, VAE, and LSTM networks to construct a personalized health management platform aimed at improving the frailty of elderly individuals. The ablation study results validate the contribution of each module to the overall system performance. GAN significantly improves the image quality and diversity of the virtual environment. VAE optimizes the reconstruction error in the personalized training model. LSTM significantly enhances the accuracy of action recognition and user experience through real-time monitoring and feedback. This demonstrates that the collaborative functioning of the modules is key to improving system performance. In health improvement assessment, although Ba Duan Jin training itself has positive effects on elderly health, the comparative experiment reveals that the personalized and real-time feedback features of this platform further enhance training effectiveness. For example, the platform group shows significantly better results in heart rate reduction, increased steps, and improved mental health compared to the traditional group. This result highlights the empowering role of technological innovation in traditional fitness methods and demonstrates that the combination of VR technology and deep learning models can significantly enhance intervention outcomes. Moreover, the immersive experience and dynamic adaptability of the platform help increase user engagement and training adherence. The personalized virtual environment better accommodates the health conditions and needs of elderly individuals by dynamically adjusting training intensity and content. This can prevent fatigue and risks associated with overtraining. The integration of social and psychological factors further improves users' mental health, which is particularly important for the elderly. However, the experimental results may be influenced by individual participant differences and other confounding variables, such as gender, baseline health conditions, and VR usage experience. Although this work attempts to control these variables through stratified randomization and standardized baseline metrics, future research should explore the applicability to different groups. Additionally, this work does not delve into the long-term intervention effects, which provides a direction for future research.

## Conclusion

### Research contribution

This work proposes a GAN-based virtual environment design method, which optimizes the GAN model to generate more realistic and diverse virtual environments. This can provide elderly individuals with a more immersive and varied training experience. Additionally, this work constructs a personalized training model based on VAE, combining elderly individuals' health data and personal characteristics to generate customized training plans, effectively enhancing training outcomes. Meanwhile, it designs an action monitoring and feedback system based on LSTM, capable of real-time monitoring and guiding the elderly's training sequences, thereby improving training safety and efficiency. This work provides a comprehensive solution for improving the frailty of elderly individuals through training, achieving significant technological progress and demonstrating important potential in practical applications. The results indicate that the proposed solution not only improves the accuracy of virtual environment generation and personalized training models but also enhances the real-time effectiveness of the action monitoring and feedback system. This provides tangible technical support for elderly health management and rehabilitation training. Moreover, the integrated solution proposed helps to promote the overall improvement of elderly health levels, offering significant social value and practical significance.

### Future works and research limitations

However, a limitation of this work lies in the limited coverage of experimental data. Future work could expand the sample size and validate the model's effectiveness and applicability in more diverse real-world scenarios. Specifically, improvements could be made to the models and methods used. Advanced generative models and optimization algorithms could be explored to further enhance the realism and diversity of virtual environments. Additionally, there is room to optimize the motion detection and feedback system and integrate more advanced technologies and algorithms to improve real-time performance and accuracy of the system.

## Data availability

The datasets used and/or analysed during the current study available from the corresponding author Jianan Dang on reasonable request via e-mail 844,981,419@qq.com .

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## Author contributions

Zhendong Yu: Conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing—original draft preparation Jianan Dang: writing—review and editing, visualization, supervision, project administration, funding acquisition.

## Declaration

## Competing interests

The authors declare no competing financial or non-financial interests.

## Ethics approval

The studies involving human participants were reviewed and approved by Nanchang University Ethics Committee (Approval Number: 2022.4095856). The participants provided their written informed consent to participate in this study. All methods were performed in accordance with relevant guidelines and regulations.

## Additional information

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