Listening to Your Heart: An AI-Empowered and Bioadaptive ASMR Audio Generation Device

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Abstract. Autonomous Sensory Meridian Response (ASMR) is a unique sensory experience triggered by specific auditory or visual stimuli, often accompanied by relaxation, pleasure and stress relief effects. People have their own preference for different ASMR audio, but current ASMR generation methods, like field collection or studio production, cannot meet various requirements. This study innovatively takes artificial intelligence-driven personalized ASMR audio generation as its core and explores its application potential in psychological regulation and physiological relaxation. We build a generation framework based on Vector Quantization Variational Autoencoder (VQ-VAE) and autoregressive model, and utilize a small amount of high-quality ASMR data to achieve deep learning and personalized generation of audio features. This model can independently synthesize high-fidelity ASMR audio with natural rhythms, friction textures and environmental atmospheres, providing users with immersive experiences tailored to their individual needs. Meanwhile, this study independently developed a set of wearable devices integrating the collection and feedback of human physiological signals, which can monitor the user's heart rate, respiratory rate, electromyography (EMG), pupil diameter and other multi-dimensional indicators in real time, thereby dynamically assessing the relaxation state and fatigue level. The experimental results show that when listening to the ASMR audio generated by AI, the average fatigue index of the subjects decreased by 32%, their heart rate and breathing rate decreased, and the pupil diameter slightly dilated, demonstrating a significant physiological relaxation effect. The innovation of this research lies in the deep integration of artificial intelligence generation models with physiological data feedback systems, achieving intelligent, adaptive and personalized generation of ASMR audio. This framework that combines AI empowerment with biological adaptability provides a new scientific basis and technical path for future digital healing, sleep improvement and emotional intervention.

Keywords: Autonomous Sensory Meridian Response (ASMR), Vector Quantization Variational Autoencoder (VQ-VAE), Emotional Intervention.

1. Introduction

Autonomous Sensory Meridian Response (ASMR) is a perceptual phenomenon. A typical response is a tingling sensation starting from the scalp and moving down the neck and spine, accompanied by relaxation and calmness [1]. Individuals report the ASMR experience when responding to auditory and visual triggers, including whispering, soft speaking, tapping, friction sounds, ambient noises and role-play scenarios that convey personal attention (Barratt & Davis, 2015; Poerio et al., 2018). Beyond relaxation, ASMR is widely known as the tool to induce sleep as the world's population suffers from sleep deprivation. Some participants describe improvements in sleep quality and reductions in anxiety when viewing ASMR videos [1, 2]. Many individuals report using ASMR videos to manage insomnia, stress, or feelings of loneliness. Some researchers also suggest that ASMR enhances internal perceptions of the body by promoting mindful attention to subtle physical sensations [3]. However, the underlying mechanisms of ASMR in inducing physical experience and its effect are largely unexplored.

One approach to investigate what components of ASMR are important in triggering the perceptual experience is to systematically generate ASMR and measure the impact through psychophysical experiments. However, this type of approach is limited in the literature. So far, most research has been conducted using audio or video clips available online, and only recently, research on algorithm-generated ASMR audio begins to address the question. For example, research generated ASMR audio focused on providing another source of ASMR other than traditional content such as YouTube videos. Though most ASMR content online are in video forms, people tend to close their eyes and listen with headphones, especially before sleep, making audio a key component of the ASMR experience. Using spatial audio design and working with immersive sound for two ears, machine-generated ASMR sound can better engage with participants as it does not require the placement or interaction of actual objects in the recording space. Additionally, increased popularity in online platforms provide high-quality sources for deep-learning models to generate their own ASMR sounds.This approach contains potential because of its ability for mass production and customization for different users. Previously, content creators made collections of audio stimuli that lasted for 20 minutes to an hour. Users have to accept the entire collection during their relaxation, despite that it includes less preferable parts. Following this trend, this study aims to contribute to newly developed algorithm-based ASMR, by producing personalized audio, even integrating into dynamic monitoring and adjusting with real-time physiological data from users.

Since this is an underexplored field, there are just a handful of previous studies on ASMR generation, reviewed as follows. Some state-of-the-art studies are included below. Fukumoto & Nan (2024) – *Interactive Evolutionary ASMR Generation* [4]. This study presents an Interactive Genetic Algorithm that composes personalized ASMR sounds by blending up to six binaural source sounds. In a user listening experiment, subjects rated each generated clip for relaxation/ASMR effect. Over successive generations, the average evaluation scores increased significantly, showing the efficacy of the model to find preferences. However, this study solely depends on subjective ratings. Fang *et al*. (2023) – *"Artificial ASMR: A Cyber-Psychological Approach."* In this study [5], The authors extract cyclic patterns from real ASMR audio and then use a Generative Adversarial Network (GAN) plus post-processing to produce artificial clips with randomized cyclic bursts. Survey data showed that GAN-generated audio can reach comparable performance to original sources. Mertes *et al*. (2023) – *"ASMRcade: Interactive Audio Triggers for ASMR."* This study [6] presents an interactive tool for ASMR generation. The authors train a WaveGAN and make users tweak inputs for customized audio. In an exploratory user study (n≈17), participants indicate ASMR-related tingles when interacting with the tool.

In terms of algorithm-based generation, the current study exceeds state-of-the-art by improving on model methodology. We suggest a VQ-VAE (Vector Quantized-Variational Auto Encoder) structure [7], increasing model robustness compared to GAN. Additionally, it breaks the dependence on user surveys by measuring psychological metrics such as heart rate, breathing rate, EMG signal and pupil size to quantitatively determine relaxation.

Apart from ASMR generation using an AI-empowered model, the current study also expands from previous research on providing systematic measurements using quantitative experiments to evaluate the impact of newly-generated ASMR instead of relying on self-reports. Previous evidence suggests some correlations between ASMR and physiological measures. For instance, Poerio et al. (2018) demonstrated that individuals experiencing ASMR exhibit decreased heart rate, breathing rate and greater skin conductance responses, indicating both subjective and physiological relaxation effects [8]. On numerous online platforms, many content creators create ASMR content for users as a relaxation tool. Table 1 below demonstrates numerous benefits of ASMR with regard to biological processing, including brain activity related to relaxation and emotions.

Tab. 1 ASMR Reference Summary

Author(s), Year	Focus	Methodology / Sample	Key Findings	Implications
Kim & Park (2024) [9]	ASMR + breathing training for mild depression	N=40 patients with mild depression; 8 sessions vs. wait-list control	ASMR + breathing group showed greater improvement in mood and depressive symptoms than the control group.	Suggests ASMR and relaxation training is a feasible alternative to alleviate depression.
Lochte et al. (2018) [10]	fMRI of ASMR experience (brain correlates)	N=10 ASMR-sensitive subjects; participants indicated tingling during ASMR video	ASMR videos activated reward/emotion areas: nucleus accumbens (NAcc), dorsal anterior cingulate (dACC), insula/inferior frontal gyrus during tingling moments.	ASMR engages brain regions associated with reward and arousal, similar to social bonding and musical “frisson”. Finding supports a neural basis for ASMR sensations.
Hozaki et al. (2025) [11]	ASMR audio/visual triggers vs nature sounds	Experiment 1: self-reported tingles; Experiment 2: N=40, measure heart rate during ASMR vs nature videos	Audio+visual ASMR videos elicited stronger tingles than audio-only (cross-modal enhancement). Both ASMR and nature clips lowered heart rate (pulse) compared to rest, but ASMR videos have a greater reduction.	Confirms ASMR’s strong relaxation effect exceeding nature sounds. The added visual component boosts ASMR intensity. Supports the “social grooming” theory stating ASMR mimics soothing social touch for stress relief.

Based on the evidence, our VQVAE-generated ASMR audio can be integrated into the platform of bioadaptive devices that can record physiological data from individuals, providing valuable readout of their level of tiredness and relaxation. This platform has great potential for customizing audio clips useful to treat insomnia and potential psychiatric issues.

2. Methods

This diagram (Fig 1) shows the integrated framework of our AI-driven personalized ASMR audio generation and physiological signal monitoring system. The core of this framework is an ASMR audio generation system based on vector quantization variational autoencoder (VQ-VAE) and autoregressive model. The specific process is as follows: AI generation model: This model generates personalized ASMR audio based on training data, extracts and quantifies audio features through VQ-VAE, and uses an autoregressive model for time series generation, ultimately producing ASMR audio that meets individual needs. User (Subject): When an individual listens to ASMR audio generated by

AI, their physiological feedback signals are monitored in real time.Physiological signal collection: Through integrated wearable devices such as heart rate sensors, respiratory rate sensors, electromyography (EMG) sensors, and pupil monitoring devices, the user's physiological state is continuously monitored. Through this innovative approach, the system can not only generate personalized ASMR audio but also dynamically adjust according to the user's physiological changes, providing the user with the best relaxation experience. This framework provides new ideas and technical paths for future applications in digital healing, sleep improvement and emotion regulation.

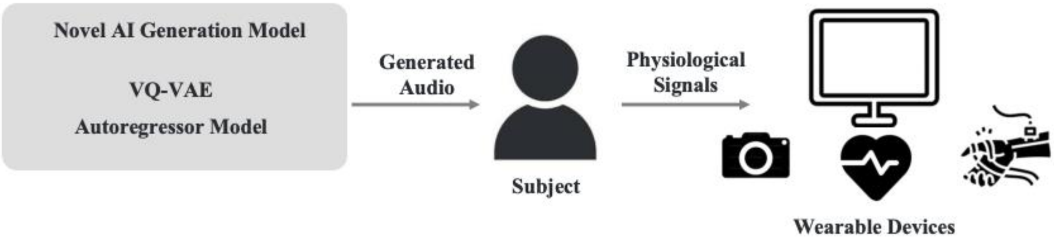

Fig. 1 The integrated framework of our AI-driven personalized ASMR audio generation and physiological signal monitoring system. (Graph created by the student researcher using Microsoft Powerpoint)

2.1. AI-Generated Audio Algorithm Framework

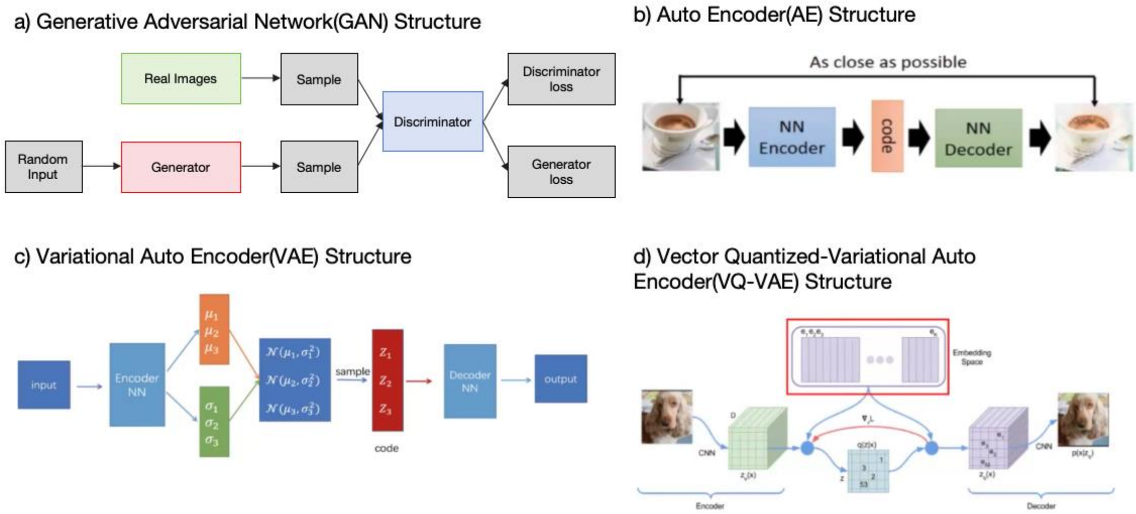

Fig. 2 The model structure of GAN(a), AE(b), VAE(c) and VQ-VAE(d). (Graph created by the student researcher using Microsoft Powerpoint)

Generative models aim to generate similar-to-real content, i.e., images, audio, video, text, etc, from random input or latent representations by learning the distribution characteristics of the data. Currently deep generative models mainly include Generative Adversarial Network (GAN) [12], Auto Encoder (AE) [13], Variational Auto Encoder (VAE) [14] and Vector Quantized-Variational Auto Encoder (VQ-VAE) [7]. This part discusses the characteristics of each algorithm with Figure X which illustrates these algorithms' structures respectively and explains the VQ-VAE model adopted in this research project (generate personalized white noise).

As shown in Figure 2a, GAN consists of two opposing neural networks: the generator network (green box) and the discriminator network (red box). The generator takes random noise as input and generates fake images through a neural network. The discriminator takes the real image and the generated image as input and outputs the discrimination result of their authenticity. Both neural networks are continuously optimized and trained through adversarial training but these two neural networks have their own training target. The generator attempts to "trick" the discriminator into generating more realistic samples, while the discriminator learns stronger detect capability regarding which one is the real image. During the training process, the objective function of GAN can be considered as a two-person zero-sum game problem, where the generator minimizes the discriminant loss of the discriminator, while the discriminator maximizes this loss. The advantage of this structure lies in the extremely high quality of the generated images. However, its training process is often unstable and problems such as Mode Collapse are prone to occur. Most importantly GAN needs a huge amount of data size to train the model and the stability of GAN extremely relies on the data quality.

The core structure of an Auto Encoder (as shown in Fig 2b) consists of an encoder and a decoder. The encoder compresses the input image into a latent space representation (red box) via a neural network. The decoder attempts to reconstruct the original image from this latent layer. The training objective of an Auto Encoder is to minimize the reconstruction error between the input images and output images, prompting the model to learn the main features of the data. The Auto Encoder structure achieves unsupervised feature learning. However, due to the lack of generative randomness, the generated images, audio or other types of content tend to be blurry or overly averaged, lacking strong generative capabilites. Therefore, it is usually used as a feature extraction or pre-training model.

The Variational Auto Encoder (VAE) introduces the probabilistic model on the basis of the traditional autoencoder, achieving generation capabilities via parameterizing the latent variable distribution. As shown in Fig 2c, each point on the latent space is described by the Gaussian distribution parameters (mean μ and variance σ) generated by the encoder. The model samples the latent variables from this distribution and then the decoder generates the corresponding contents. The objective function of VAE consists of two parts: reconstruction error (the difference between the reconstructed image and the original image) and Kullback–Leibler(KL) divergence(to make the latent variable distribution approach the standard normal distribution), building a balance between the generated image quality and the interpretability of the latent space structure. However, due to the strong regularization constraint of KL divergence, the contents generated by VAE, such as text, images, or music, often appears lacking in detail, compared to other generative models.

Vector Quantized-Variational Auto Encoder (VQ-VAE) introduces discrete latent variable modeling and the vector quantization mechanism based on the VAE framework. In the VQ-VAE structure (as shown in Fig 2d), the encoder first maps the input image to a continuous latent representation, and then finds the closest vectors in the embedded codebook. This process can be considered as a discretization process, i.e., dividing a continuous space into several finite vectors. The decoder then applies these vectors to reconstruct the output image, audio or other kind of content. The training objective of VQ-VAE consists of three parts: reconstruction loss, quantization loss, and dictionary update loss, to ensure that the distribution of the encoded vectors is consistent with the dictionary embedding. Compared with VAE, VQ-VAE not only can generate clear and detailed content, but also avoids the unstable training problems in GAN.

Given that our research focuses on the white noise generation and the limited computing resources for high school students, we should apply few-shot data sample size training. In Table 2 summarize the characteristics of different generative models based on previous analysis. VQ-VAE can achieve high robustness and conditional modeling capability respectively via discrete representation. In addition, the discrete latent variable structure of VQ-VAE provides a natural symbolic input for the subsequent use of autoregressive models for latent space modeling, enabling the model to perform well in multimodal generation tasks such as image, speech, and video. In summary this research applies VQ-VAE with autoregressive models for white noise generation.

Tab. 2 The Comparison for GAN, AE, VAE and VQ-VAE

Model	Theory	Few-shot Robustness	Conditional Modeling Capability
GAN	Adversarial Learning	Low	Strong
AE	Representation Learning	High	Weak
VAE	Variational Inference	Medium	Relatively Strong
VQ-VAE	Discrete Representation	High	Strong

2.2. Device Development

This study requires biological data from human subjects, including human eye pupil diameter, heart rate, respiratory rate, and electromyography (EMG) to measure the current level of fatigue. The hardware used in the study and its connections are shown in the Figure 3 below.

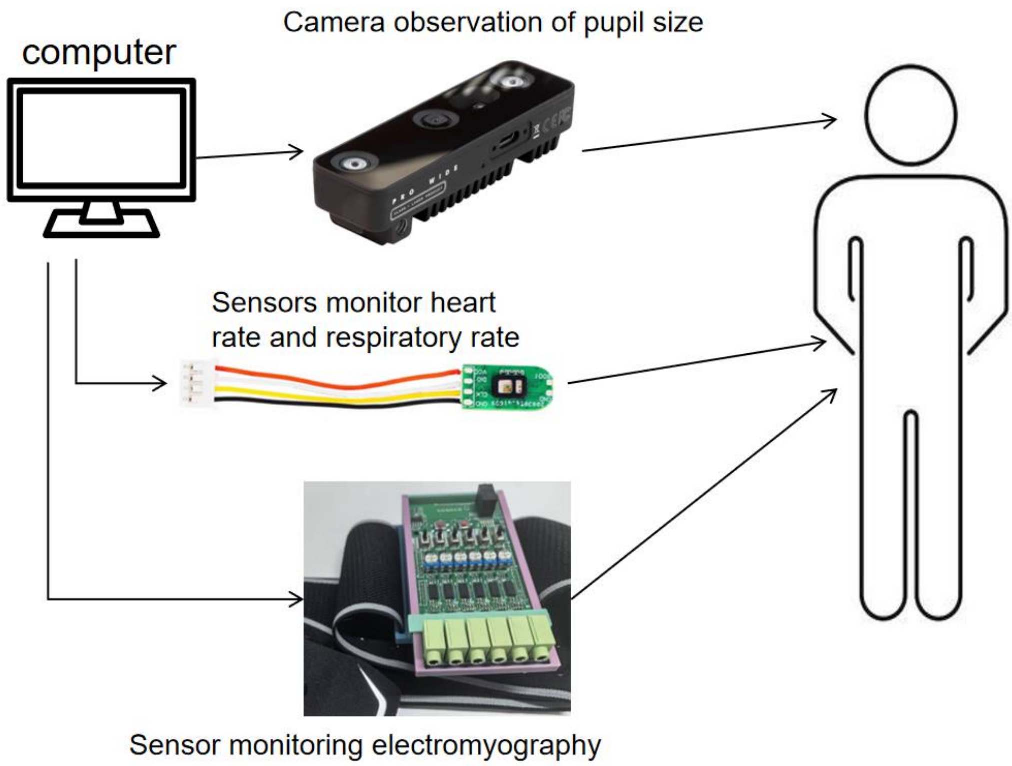

Fig. 3 The structure of hardware system (Graph created by the student researcher using Microsoft Powerpoint)

The size of the pupil is a recognized indicator of the degree of arousal and engagement of the individual, reflecting the state of the body. For example, as one's degree of fatigue increases, the diameter of the pupils of both eyes tends to decrease consequently.

This study used a camera, positioned at the center of the two ears, to capture the facial images of participants. It employed the Mediapipe Face Landmarker task to detect key point information in the face, including estimates of approximately 478 3D facial feature points. The pupil key points were located using the coordinates [474,475,476,477] of the left pupil and [469,470,471,472] of the right pupil. Based on the pre-input actual distance between the ears, the true pupil size was calculated (see Figure 4). Pupil size was used as an indicator to measure user fatigue.

Fig. 4 Detecting pupil diameter (Graph created by the student researcher using a selfie camera)

In addition, we have prepared tools for measuring human heart rate and respiratory rate(see Fig 5), an integrated small portable sensor equipped with a self-designed and 3D-printed shell, which ensures that the device can be worn directly on the user's finger, realizing portable measurement.

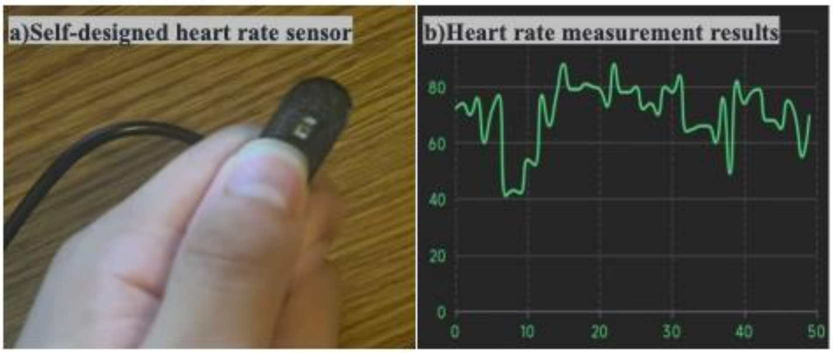

Fig. 5 Self-designed heart rate sensor and heart rate measurement result (Graphs created by the student researcher using camera(a) and screenshot(b))

The sensor integrates red, infrared, and green LEDs. It can switch between different detection modes for different body parts, such as fingertips or wrists. It can accurately measure heart rate, blood oxygen saturation, and respiratory rate. Heart rate is a major factor affecting fatigue levels. A normal adult heart rate is approximately 60-100 bpm. A heart rate higher than 100 bpm may indicate a rapid heart rate, often caused by emotional stress or excessive fatigue.

Furthermore, the RMSSD value is also an important indicator of fatigue. RMSSD is an abbreviation for "the square root of the mean square of the difference between consecutive normal sinus beats." Simply put, it is a key time-domain indicator for measuring heart rate variability and is widely considered one of the "gold standards" for assessing parasympathetic nervous system activity. It is calculated by summing the squares of the differences between two adjacent heartbeat cycles (RR intervals), taking the average, and finally taking the square root. The formula is:

$$RMSSD = \sqrt{[(1/(R-1)) * \sum_{1}^{n} \quad (RR_{n+1} - RR_n)^2]} \tag{1}$$

The formula reflects the rapid, instantaneous changes in heart rate between heartbeats. The instantaneous heart rate fluctuations caused by breathing are the main object of RMSSD measurement. The core physiological significance of RMSSD lies in its direct reflection of the activity of the parasympathetic nervous system, which is responsible for relaxing the body, conserving energy, lowering heart rate, promoting digestion, and recovery. When the RMSSD is active, the body is in a state of repair and regeneration. A high RMSSD indicates a strong parasympathetic nervous system, capable of quickly recovering from stress, while a low RMSSD indicates chronic stress or over-fatigue. Therefore, using algorithms to collect heart rate data, calculate cycles, and determine the RMSSD value will be an important factor in assessing the level of physical fatigue.

Electromyography (EMG) signals can indirectly reflect fatigue levels. When a person is fatigued, the central nervous system alters the nerve signals that drive muscles, leading to decreased muscle coordination. This results in increased muscle tension, which is reflected in a steeper curve on an EMG chart. By using EMG to assist in determining the current state of fatigue, and combining this with previously observed pupil size and heart rate characteristics, a more accurate assessment of fatigue can be obtained.

2.3. Subjects & Experimental procedures

There were 10 healthy human participants in total, with 6 males and 4 females. There were 8 participants in the age range of 17-25, and 2 participants in the age range of 40-50. Volunteers are recruited from family members, myself and student volunteers at the Webb Schools.

The experimental procedure is described in Figure 6. To test the impact and efficacy of machine-generated ASMR audio on human relaxation, participants will sit and listen to ASMR audio wearing headphones. Meanwhile, the participant will be wearing surface EMG electrodes and a heart-respiration rate sensor. A camera will be positioned in front of the participant to capture his/her pupil size.

Before conducting the experiment, the participant will sign the Informed Consent Form and fill out the pre-ASMR survey. Then, the participant will go through two cycles of 1-minute rest and 1-minute ASMR stimuli to observe the impact of ASMR on psychological signals. This A-B-A design was on purpose, aiming to recapitulate any physiological changes induced by the ASMR experience in the 2nd measurements. After the experiment, the participant will fill out the post-ASMR survey. The experiment should be of minimal risk, with the only concern being some mild discomfort while wearing electrodes. The subjects are allowed to quit the experiment if reporting discomfort.

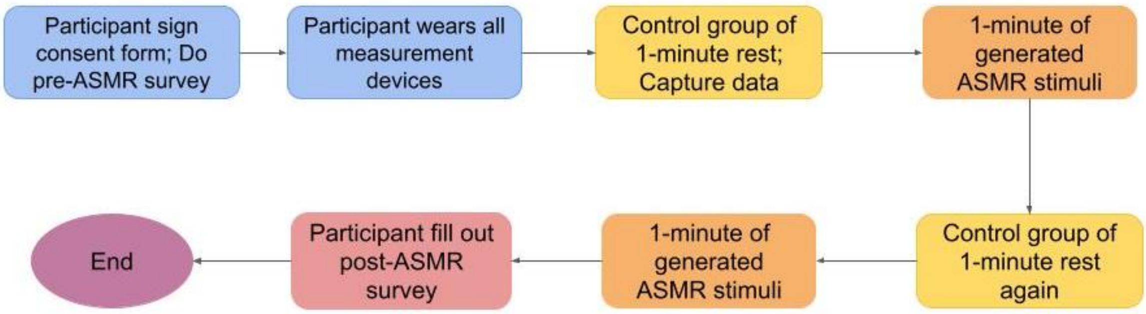

Fig. 6 The experimental procedure (Graph created by the student researcher using Microsoft Powerpoint)

3. Main results

3.1. The AI-Generated Audio

Based on the previous analysis, we trained a generation system that combines VQ-VAE (Vector Quantization variational Autoencoder) and the autoregressive model to generate audio with ASMR features. The focus is on capturing sound characteristics such as rhythm, frictional texture and ambient atmosphere. The training data is derived from the YouTube-ASMR-300K dataset. From this large corpus, we selected 1,500 audio samples, covering four categories: percussive sounds, friction, vocals and environmental music.

The model structure adopts the one-dimensional convolutional VQ-VAE encoder-decoder (1D-convolutional VQ-VAE encoder-Decoder) implemented by us, and combines with the GPT-style autoregressive sequence generator. The VQ-VAE module uses Residual Finite Scalar Quantization to encode the original audio into discrete latent representations (levels = [8, 5, 5, 5]; The embedding dimension is 512, and the autoregressive module models the temporal dependencies among these discrete tokens through a multi-layer cross-conditional self-attention mechanism. During the entire system training process, cross-entropy loss is adopted for token prediction, and L1 reconstruction loss is combined to optimize the audio reconstruction effect. As shown in Figure 7, the training loss steadily decreases over time and tends to converge, indicating that the model learning process is stable and effective.

After the training was completed, the model successfully generated audio samples with diverse ASMR features. The generated audio exhibits coherence and natural rhythmic transitions in terms of temporal structure, and maintains texture consistency in perception: the percussion sample shows a clear undulation structure (attack-decay), the friction vocals display a true granular texture, while the ambient music segments have the characteristics of smooth and continuous atmospheric flow.

Overall, the experimental results show that combining the discrete latent representation ability of VQ-VAE with the autoregressive time series modeling framework can effectively learn the high-level temporal structure and fine-grained acoustic features of audio even under the condition of using only 1,500 data samples and limited computing resources. This method offers a feasible and promising direction for personalized white noise audio modeling.

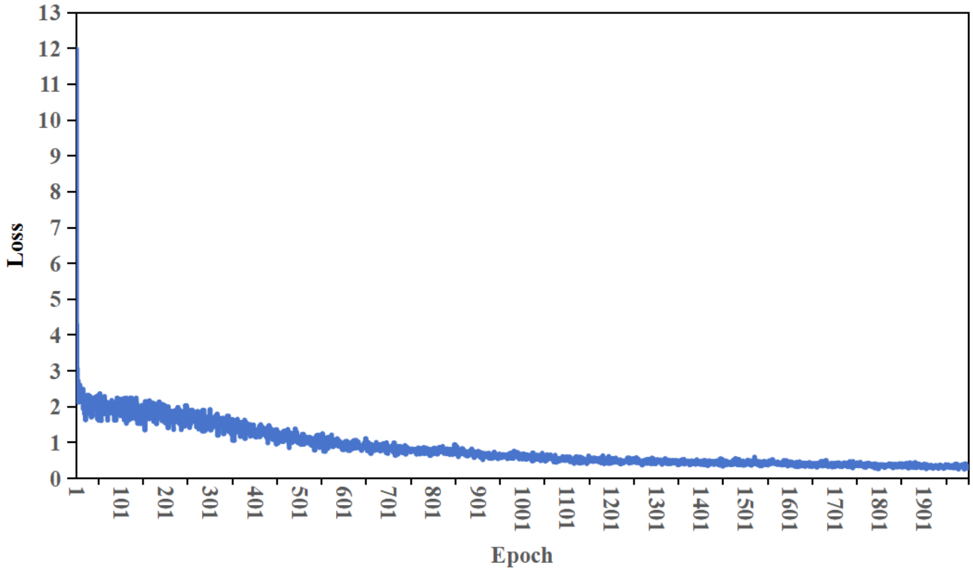

Fig. 7 The Loss-Epoch graph for AI model (Graph created by the student researcher using Python)

3.2. Behavioral experimental results

For behavioral experiments, it is clear to establish that generated ASMR has benefits for participants. Figure 8 also demonstrates the example user interface when collecting physiological data. From heart rate and breathing rate sensors, though there are slight decreases for heart rate and breathing rate, the fatigue index is the metric with most significant changes. Across all participants, the fatigue index decreases by 32% when exposed to generated ASMR stimuli compared to staying at rest, as shown in Figure 9 below.

Observing EMG data collected at two inner elbows and the neck, the data is mainly chaotic and does not show a consistent pattern across participants. Most data surrounded the range of resting muscle and light contraction, possibly due to the fact that participants were sedentary and did not involve a lot of physical movement when collecting EMG data. However, it is a good sign to see that participants are staying in a relaxed state throughout the duration of the experiment.

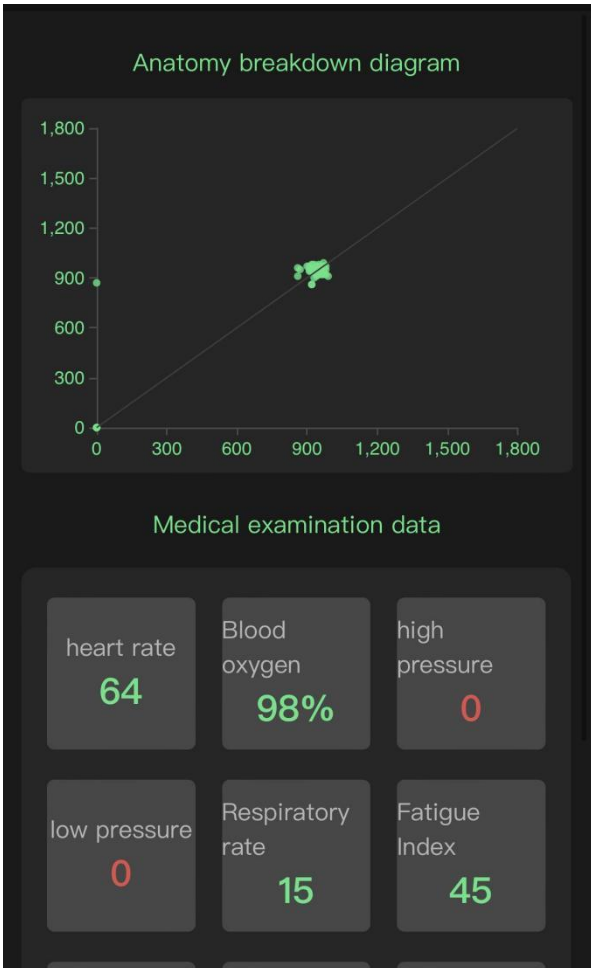

Fig. 8 The user interface when collecting physiological data. (Graph created by the student researcher using screenshot)

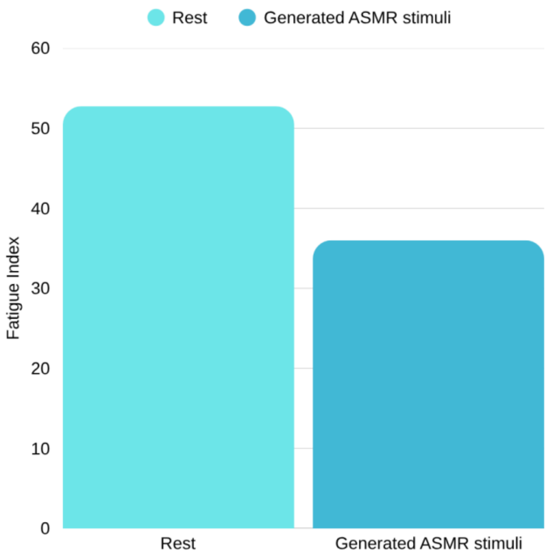

Fig. 9 The generated ASMR stimuli compared to staying at rest (Graph created by the student researcher using Python)

Another aspect of measuring degrees of relaxation is by pupil sizes. In the two cycles of experiments, when taking the average of both pupils across all participants, there is a clear dilation in participants under the exposure of generated ASMR and contraction when not exposed to ASMR. Additionally, we can observe from the second rest period that participants demonstrate a tendency towards relaxation even after listening to generated ASMR, creating a lingering effect on their mental and emotional states. Figure 10 below summarizes data trends for pupil sizes across all participants. The change might not appear as very significant, but it is crucial to acknowledge that pupil contraction and dilation are very limited motions. Illustrating a clear pattern for the average of all participants does require significantly more relaxed states.

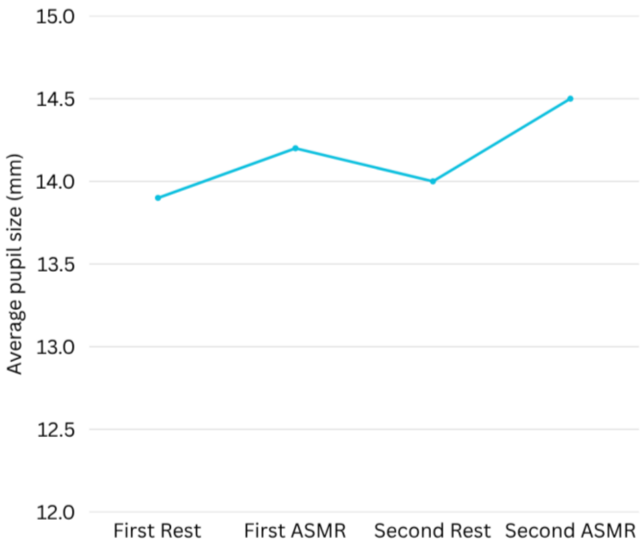

Fig. 10 Trends for pupil sizes across all participants (Graph created by the student researcher using Python)

And of course, participants demonstrated positive feedback towards this experience in the survey, and some reported their first ever ASMR response during this experiment.

To summarize, the generated ASMR proved its efficacy through multiple aspects of physiological data, including the decrease in heart rate and level of fatigue during ASMR experience and pupil dilation even after stimuli. However, it is uncertain whether the physiological changes are attributable to ASMR experience only. From the experimental setup, it is possible that having participants sit still and clear their minds could alleviate levels of stress and induce relaxation already, with ASMR just being a further propellor of that effect. Additionally, this study can also benefit from longer experiment times, tracing the states of participants longer after they listen to generated ASMR and having them listen to longer clips in general. More participants can also enhance the credibility of the study and show that our findings are not coincidental due to a small sample size.

4. Discussion

Summarise main results (VQVAR model, review the approach novelty, precise measurements through experiment)

The current study has advanced the emerging field of using algorithm-based methods to generate ASMR for customized experience, combining AI tools with objective physiological measurements through experiments. Distinct from previous studies relying on subjective evaluations of tingling experience, here we integrate quantitative metrics including changes in heart rate, respiration, EMG signal and pupil size. Our integrated model not only promotes the flexibility of ASMR audio, but also enables production of personalized ASMR experiences that are biologically adaptable. Although bearing some limitations in the current stage, combining the physiological metrics as clear readout of ASMR, this framework offers a loop for real-time optimization to tailor an individual's perceptual experience and behavioral state.

Moreover, the implication of our work can extend beyond the technical development of ASMR generation. ASMR can be used not only for entertainment or relaxation as media, it also has potential for both research use and clinical use such as treatment of sleeping issues and mental health issues. On the one hand, manipulating ASMR stimuli by incorporating different features provides a powerful database and paradigm to dissect the mechanisms of how sensory and affective components may interact. Research of neuroscience could combine cutting-edge techniques such as the functional magnetic resonance imaging to study ASMR induction and multimodal perception at neuronal level. On the other hand, it opens opportunities for translational applications in sleep improvement, emotion regulation and stress management. Future implications could adopt this AI-empowered and bioadaptive ASMR generation platform to intervene in issues of mental wellbeing.

5. Conclusion

In summary, our study contributes to the underexplored but emerging field of AI-generated ASMR by demonstrating a framework, which achieves personalized sound synthesis through VQ-VAE and effect evaluation through physiological metrics. This approach offers a new perspective to combine algorithmic design and objective evaluation for studying ASMR experience and mechanisms. Importantly, we believe that our model opens possibilities for personalised, adaptive biological and psychological experience, providing broader implications in promoting mental health through digital interventions.

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