Computer Interaction Methods and Modes for Epilepsy Patients

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Keywords: Epilepsy, Human-Computer Interaction, Brain-Computer Interface, Artificial Intelligence, Smart Wearable Devices.

Abstract: Epilepsy is one of the most common chronic neurological disorders worldwide. Traditional drug therapies have limited effectiveness for such patients and long-term use may lead to side effects such as cognitive impairment and metabolic disorders. In addition, patients face unpredictable seizure risks, traditional nursing methods have limitations in evaluation and treatment effect, there are many technical aspects of epilepsy patients that can be optimized, and innovative technological breakthroughs are urgently needed to break through the existing bottlenecks. This paper reviews the application of brain-computer interfaces (BCIs), multimodal interaction technologies, artificial intelligence (AI), eye-tracking, and smart wearable devices in epilepsy management. It also proposes future research directions, including multimodal data integration, nanoscale brain-computer interface (BCI) development, patient-participatory design, and ethical privacy protection. These innovations aim to enhance diagnostic accuracy, enable personalized treatment, and improve daily monitoring for epilepsy patients, thereby boosting their quality of life and advancing the medical field toward greater intelligence and precision.

1 INTRODUCTION

Epilepsy is a prevalent neurological disorder affecting approximately 70 million people globally (Zhao et al., 2020). It is a chronic condition with a broad impact, recognized by the World Health Organization as one of the five key neurological and psychiatric diseases requiring global prevention and control (Beghi et al., 2019). Patients face challenges such as seizure-related quality of life issues, reliance on technological devices, and device design inadaptability. Advancements in smart devices and technologies aim to improve patients' lives, prompting extensive research into epilepsy-specific human-computer interaction (HCI), particularly in interface and modality design. BCIs offer closed-loop neural regulation by decoding brain signals, such as implantable systems that suppress abnormal discharges and reduce seizure frequency, and non-invasive devices like lightweight (1.7g) head-mounted microscopes that monitor neural activity and blood oxygen metabolism, capturing pre-ictal neurovascular signals. The integration of BCIs, multimodal interaction technologies, and AI provides new avenues for epilepsy monitoring and intervention. Multimodal technologies enhance system adaptability and patient compliance by combining visual, auditory, and tactile data. For instance, eye-tracking combined with ear-worn electroencephalography(EEG) devices enables home seizure warnings with 99.8% accuracy. AI algorithms play a key role in multimodal data analysis, predicting drug responses and optimizing doses through EEG and genomic data fusion. Additionally, optogenetics and gene therapy (e.g., adeno-associated virus-delivered neuropeptide Y) offer molecular-level seizure control. Despite progress, challenges remain in multimodal data integration, device miniaturization, biocompatibility, and ethical and privacy risks. Future research should focus on interdisciplinary innovation, such as nano-flexible electrode development for reduced tissue damage and long-term BCI implantation, patient-involved design for improved device comfort and interfaces, and ethical frameworks for neural data usage regulation.

This paper analyzes existing work, its effects, and shortcomings, explores the characteristics and needs of epilepsy patients, and discusses emerging research directions.

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2 EXISTING WORK AND ITS EFFECTS

With the rapid development of artificial intelligence and machine learning, the collaboration between computer and medical fields have become increasingly prominent in epilepsy research (Li et al., 2024), as shown in figure 1.

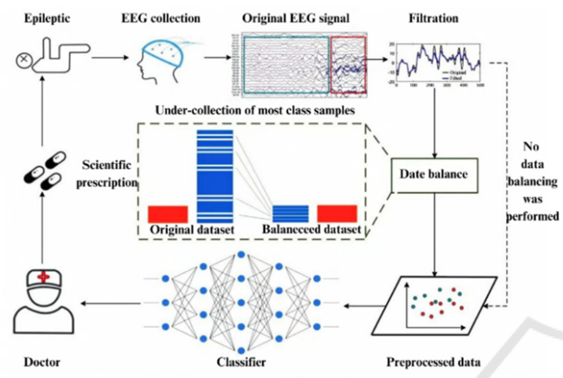

Figure 1: Computer collaboration process (Li et al., 2024).

2.1 Brain-Computer Interface (BCI)

BCI devices collect brain activity data, transmitting it to computer terminals for decoding algorithm research. BCIs are highly valuable for real-time epilepsy monitoring, prediction, and intervention, offering personalized treatment (Chen, 2025). Clinical techniques include EEG, magnetic resonance imaging(MRI), and PET-CT (Zhang, 2022). Implantable or non-invasive BCI devices (e.g., cortical electrodes, EEG headsets) continuously collect EEG data, using AI algorithms to identify pre-ictal abnormal discharges. Some BCIs can provide warnings minutes to hours before seizures, helping patients take safety measures.

2.2 Multimodal Interaction Technology

This technology combines EEG, EMG (electromyogram), visual, and auditory data sources to comprehensively reflect patient behavior, improving epilepsy monitoring accuracy and severity assessment. It also aids diagnosis based on seizure observation and etiology (NICE, 2022). Adaptive PageRank algorithms assess brain region importance, considering interactions between regions, while multi-kernel strategies address data heterogeneity by integrating connectivity and node information for classification (Frontiers, 2021). The system comprises three main modules: EEG data acquisition, cloud-based analysis, and monitoring/decision support. EEG data is collected, transmitted wirelessly to the cloud for analysis using machine learning, and results are fed back to support treatment planning and home epilepsy management, as shown in Fig. 2.

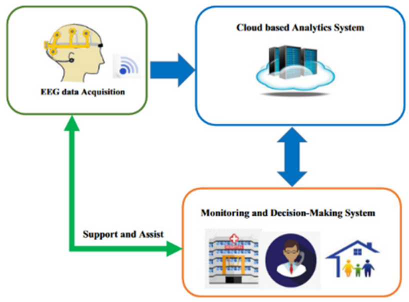

Figure 2: Basic components of the automatic seizure detection system (Picture credit: Original).

Epileptic seizure physiological signals exhibit spatiotemporal heterogeneity, making single-modal data (e.g., EEG) susceptible to noise and insufficient for comprehensive condition reflection. Multimodal technology integrates EEG, EMG, motion sensors (accelerometers, gyroscopes), visual behavior analysis (cameras), and other physiological indicators to build multidimensional feature models. For example, combining EEG and motion analysis enhances detection sensitivity for tonic-clonic seizures to 100% through deep learning algorithms like convolutional neural networks(CNN) and long short-term memory networks(LSTM). Synchronized monitoring of multiple physiological parameters, such as skin conductance activity (EDA), electrocardiogram (ECG), and EEG, captures sympathetic nervous system excitement during seizures, reducing missed detections (Ein Shoka et al., 2023). Cross-modal alignment techniques, such as ResizeNet networks, address cross-species EEG signal differences and feature distribution shifts, improving model generalization.

2.3 Artificial Intelligence (AI) in Epilepsy Human-Computer Interaction

AI algorithms play a crucial role in epilepsy prediction, diagnosis, and rehabilitation. By integrating EEG, ECG, and genomic data, they construct personalized treatment models. Deep learning models (e.g., CNN, LSTM) excel in EEG signal analysis, identifying pre-ictal sharp waves with 98.72% sensitivity and 91.17% F1 score (Yu, 2021). Transfer learning frameworks address interindividual EEG differences, enhancing classification performance. AI predicts drug responses and optimizes doses, such as HCN1 channel-based precision drug design. Google Health's AI model can predict seizures an hour in advance with 85% accuracy. AI also provides personalized treatment plans by analyzing EHRs (electronic health records) and multimodal data. Lin's team proposed a machine learning-based prediction model for epilepsy patients with cognitive impairment (Lin et al., 2021).

The suggested framework consists of three collaborative stages:

Stage 1: IoT-based wearable medical sensors and smartphones collect real-time data, connecting to patients' EEG data collectors.

Stage 2: Cloud computing provides processing and storage resources, receiving patient data via the internet for classification and analysis. Abnormalities are classified based on patient status, and results are reported to healthcare providers, enabling early drug intervention and real-time data updates.

Stage 3: Medical staff monitor patient records and EEG data via cloud-based networks, review reports, and take appropriate actions. BCI devices collect brain activity data, transmitting it to computer terminals for decoding algorithm research.

2.4 Eye-Tracking

Eye-tracking technology controls devices through eye movement, offering precise input for epilepsy patients unable to use hands or voice. Eye-trackers are categorized into head-mounted and desktop types (Zhang, 2022), as shown in Fig. 3.

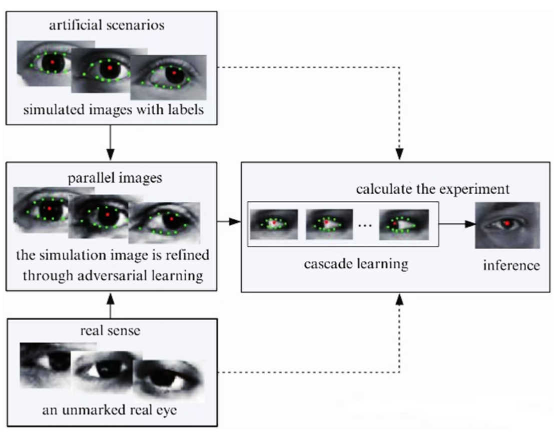

Figure 3: Learning process of eye tracking (Zhang, 2022).

2.5 Smart Wearable Devices

Smart bands, watches, and other wearables record physiological data like skin conductance, temperature, pulse, and motion, using LSTM networks to predict seizures. They provide real-time monitoring and feedback for self-management. A facial expression recognition system based on novel flexible piezoresistive materials captures pressure signals from facial muscle and skin deformation via sensors in eyeglass legs, enabling emotion classification (Zhang & Xing, 2025), as shown in Fig. 4.

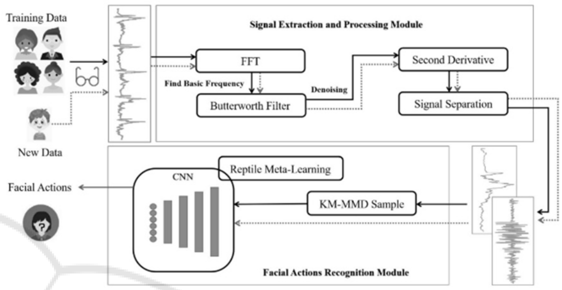

Figure 4: The workflow of our system (Zhang & Xing, 2025).

3 SHORTCOMINGS OF EXISTING TECHNOLOGIES

3.1 Challenges of BCI Systems in Epilepsy Applications

The spatiotemporal complexity of epileptic discharges demands high algorithm accuracy for signal decoding. The imbalance between inter-ictal and ictal EEG data leads to high accuracy for non-seizure data but poor recognition of seizure data, causing false positives and missed detections. Future algorithms must improve minority sample recognition (Wang & Zhang, 2022). This imbalance makes classifiers prone to false positives and missed detections in practical applications, affecting the accuracy and reliability of epilepsy seizure prediction. In the future, more efficient and robust algorithms need to be designed to address this issue, enhancing the ability to identify minority class samples, thereby improving the precision and reliability of epilepsy seizure prediction (Xiaohui et al., 2024).

Long-term device stability is also an issue, with implantable electrodes suffering signal attenuation

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due to tissue encapsulation and non-invasive devices being prone to motion artifacts. Moreover, individual differences in seizure foci and types require highly customized algorithms and stimulation parameters. Pediatric patients' dynamically developing brains further complicate BCI parameter adjustment, necessitating personalized algorithms and timely parameter updates.

3.2 Challenges in Multimodal Data Fusion

Multimodal data heterogeneity is a significant challenge. Differences in time resolution, spatial features, and semantic associations across modalities (e.g., EEG, MRI, ECG) complicate data fusion. Ambiguous semantic links between genomic and imaging data require complex algorithms, yet current methods struggle to capture high-order heterogeneity, risking information loss and poor fusion outcomes. In clinical settings, modality missingness adaptation is insufficient. Many multimodal systems rely on complete data inputs, so missing key modalities due to privacy, technical, or cost constraints degrades system performance. This limits clinical application and adversely affects diagnosis and treatment. Cross-modal relationship modeling is further complicated by difficulties in spatiotemporal alignment of heterogeneous data. Existing algorithms often fail to capture high-order associations between such data. For example, structural and functional brain networks provide different perspectives on epilepsy-related structural changes, but common fusion models only integrate information at a single granularity, ignoring the multi-granular nature of brain networks and leading to suboptimal fusion effects (Qi et al., 2024).

To address these challenges, researchers are exploring new methods. For instance, the alternating single-modal adaptation (MLA) method optimizes each modality's encoder while integrating cross-modal information to reduce interference and enhance fusion performance. For modality missingness, robust multimodal learning methods like MoRA are being developed, which insert specific modules to identify missing modalities and improve model robustness under extreme missingness conditions (Xiaohui et al., 2024).

3.3 Limitations of AI Epilepsy Early Warning Systems

Real-time response delays and data bias/fairness issues are two major challenges for AI in epilepsy prediction. AI systems often rely on historical data for predictions, which limits their ability to respond dynamically to sudden epileptic events. For example, epilepsy seizures are often sudden and unpredictable, yet AI systems require time to process new data and update models, potentially missing optimal intervention timing. To enhance real-time responsiveness, researchers are investigating new algorithms and architectures, such as deep learning-based real-time prediction models and edge computing technologies to accelerate data processing.

Regarding data bias and fairness, training data is often regionally and demographically skewed, with most data originating from Western patients. This results in reduced accuracy and applicability for specific groups like children and ethnic minorities, potentially exacerbating healthcare disparities. To mitigate this, researchers recommend using more representative datasets and developing adaptive algorithms. Cross-institutional and international data sharing can also help create more comprehensive and balanced training datasets.

3.4 Impact of Different Environments and Application Scenarios on Eye-Tracking Effectiveness

Eye-tracking technology faces multiple challenges in practical applications, including poor environmental adaptability, insufficient real-time responsiveness, and interference signals. Under complex environmental conditions, such as low light or high reflection, eye-tracking technology often underperforms. In such cases, single-modal eye-tracking data struggle to maintain system stability and accuracy, necessitating multimodal data fusion technology to enhance overall performance. By integrating data from different modalities, such as environmental sensor data or other biometric data, the shortcomings of single-modal data can be effectively addressed, improving the adaptability and robustness of eye-tracking systems in complex environments.

The insufficient real-time responsiveness also restricts the application of eye-tracking technology in scenarios demanding high response speeds. For instance, delays in eye-tracking can degrade user experience and even pose safety risks in autonomous driving or real-time interaction systems.

Interference signals are another significant challenge for eye-tracking technology. Physiological phenomena like eye jitter and blinking can cause data interruptions or misjudgments, affecting system accuracy and reliability. To tackle this issue, researchers are developing advanced signal processing algorithms to identify and filter out interference signals. Additionally, improving the design of eye-tracking devices, such as using more precise sensors and optimized optical systems, can help reduce the impact of interference signals.

3.5 Hierarchical Security Protection and Attack Path Analysis of Wearable Devices

Missed detection of focal and non-motor seizures, edge computing bottlenecks, and digital security risks are key challenges for wearable devices in epilepsy monitoring.

Wearable devices (e.g., wristbands) are highly sensitive to tonic-clonic seizures, achieving 100% detection accuracy when combining EEG and ECG, but have low recognition rates for complex partial or absence seizures, with missed detection rates exceeding 50%. Focal autonomic seizures or absence seizures lack significant physiological or motor features, making them hard to detect. Existing devices are less effective for these seizure types.

Edge computing bottlenecks constrain device performance. High-precision AI models (e.g., Transformers) consume significant power on wearables, creating a trade-off between performance and battery life. Researchers are exploring efficient algorithms and hardware optimizations to reduce energy consumption and enhance computational efficiency.

Digital security risks are a concern. Wearable devices require layered protection from hardware to application levels. Threats penetrating network boundaries can compromise hardware and system layers, jeopardizing application service and data security. This may lead to digital asset risks and potential post-attack denial by attackers (Zhao et al., 2024). Device manufacturers need to strengthen security measures, such as advanced encryption, regular security patches, and user education.

4 CHARACTERISTICS AND NEEDS OF EPILEPSY PATIENTS

4.1 Disease Characteristics

Epilepsy patients face multiple challenges: seizures are sudden and unpredictable, with irregular occurrence and duration, potentially causing transient loss of consciousness, motor control, or sensory impairments. This increases the risk and difficulty of using electronic devices. For instance, patients may lose control during seizures or be unable to recall operations afterward. Epilepsy is chronic and recurrent, requiring lifelong management. About 30% of patients develop drug-resistant epilepsy, necessitating surgical or neuromodulation options. Epileptic symptoms are diverse, including generalized convulsions and brief loss of consciousness, with varying impacts on daily life.

4.2 Physical and Cognitive Effects

Epileptic seizures pose significant physical injury risks, such as falls and suffocation, potentially leading to fractures or traumatic brain injuries. Frequent seizures or medication side effects often result in memory decline and attention deficits, particularly in children. world health organization (WHO) data indicates that 40%-60% of epilepsy patients experience anxiety or depression, facing substantial psychological and social pressures. Stigma and psychological burdens lead many to conceal their condition, while school and workplace discrimination create additional challenges.

4.3 Core Needs of Epilepsy Patients

The needs of epilepsy patients stem from disease characteristics and social biases. A comprehensive support system covering "prevention-treatment-integration" is required.

Epilepsy management must be multidimensional. Precision medical support is essential, starting with early diagnosis and correct classification. Individualized treatment plans should be developed, with drug-resistant patients trying alternative therapies like neurostimulation or the ketogenic diet. Treatment plans should be dynamically adjusted. For safety and emergency care, patient environments should be safety-adapted, and scientific first aid knowledge should be promoted. Special groups have unique needs: children require cognitive rehabilitation and personalized educational support (e.g., Cambridge University's "EpiSchool" AI platform for customized learning paths); women of childbearing age need pregnancy medication guidance and genetic risk counseling; elderly patients, often with multiple comorbidities, require hospital-based comorbidity management and family monitoring with home safety modifications.

5 DISCUSSION AND ANALYSIS

5.1 Multimodal Interaction in Home and Medical Settings

5.1.1 Multimodal Data Integration

Real-time monitoring data from EEG, ECG, EMG, and wearables (smart bands/clothing). Cameras capture limb movements, and voice interactions are recorded. Environmental data such as temperature, humidity, and intensity of illumination in homes and public places are also collected. Integrating these data sources creates a comprehensive patient data profile throughout the life cycle.

5.1.2 Subjective Feedback

Voice diaries and emotion recognition (via NLP to detect anxiety/depression) from patients and families. Combined with genetic data, medication history, and multimodal monitoring results, dynamic medication suggestions (e.g., dosage adjustment or drug switching) are generated. Timely medication reminders, sleep advice, and seizure trigger avoidance (e.g., staying up late, strong light stimulation) are provided to help patients establish regular routines. Disease causes, first aid measures, and treatment progress are explained in layman's terms to alleviate patients' fears stemming from misunderstandings.

5.1.3 Smart Home Integration

During a seizure, AI systems recognize falling motions via cameras, automatically shutting off gas, dimming lights, and activating emergency calls. Smart home devices provide vibration or voice prompts to patients ("You are about to erupt. Please sit down ") and send location information to family members.

5.2 Emerging Research Directions

5.2.1 Multisensor Fusion for Early Warning

Devices integrate motion sensors (detecting abnormal convulsions), skin conductance sensors (monitoring stress levels), and microphones (identifying abnormal breathing sounds). Edge computing enables real-time analysis and alarm triggering. Upon detecting abnormal EEG signals, emergency procedures are initiated, contacting emergency contacts or medical institutions automatically. Seizure times and symptoms are recorded for doctors' reference.

5.2.2 AR/VR + Dialogue Robots for Rehabilitation Training

AR simulates high-risk scenarios (e.g., crossing roads) to train patients in self-protection actions upon recognizing premonitory symptoms. VR provides relaxing environments to alleviate anxiety (e.g., meditation forests) and simulates social interactions to boost patients' confidence and social engagement.

5.2.3 Doctor-Patient Remote Collaboration

Patients can film seizure videos with their smartphones. AI automatically marks key frames (e.g., tonic-clonic phases), enabling doctors to diagnose quickly combining voice descriptions. This is applicable for emergency handling and daily monitoring, reducing safety risks for patients going out alone and saving time for both doctors and patients. It also provides more convenient and equitable medical support for remote patients.

5.2.4 Nano-BCI

Nano-particles or flexible electronics enable non-invasive, high-precision monitoring, reducing the immunoreaction to implantable BCIs and increasing patient acceptance.

5.2.5 Brain-Cloud Interface

Epilepsy patients can upload EEG data to the cloud in real-time. After verification, the system synchronizes data to doctors' platforms. Qualified physicians can access and analyze global patient data online for monitoring, diagnosis, and treatment.

5.3 Patient-Centered Design

Epilepsy can cause cognitive impairments and tendencies toward depression and anxiety. It is crucial not only to enhance technologies for predicting and diagnosing epilepsy but also to monitor patients' emotions in real-time to prevent worsening conditions or impulsive negative behaviors. Automatically adjusting interaction methods and feedback based on patients' physiological and psychological characteristics to provide customized user experiences represents a future research challenge.

5.3.1 Emotion Recognition and Guidance

Natural Language Processing (NLP) analyzes anxiety, depression, or loneliness in patients' speech, offering immediate comfort such as guided mindfulness exercises, relaxation techniques, or referrals to professional psychological resources. It is necessary to train models to distinguish between pathological and psychological emotional changes to avoid misjudgments. For patients with social limitations due to their condition, robots can reduce loneliness through daily conversations and encourage emotional expression.

5.3.2 Personalized Adaptation

Customize dialogue content based on patients' age, severity, and cultural background. Combine voice, text, and visual interfaces (e.g., animated breathing guidance) to accommodate different communication preferences. Incorporate patient feedback during development to optimize interface and functionality adaptation.

5.3.3 Affective Computing and AI Companionship

Voice emotion recognition (e.g., tone, speed) and facial expression analysis enable AI chatbots to provide real-time psychological support. Combined with soothing music, dynamic lighting, and tactile feedback (e.g., pressure blankets), anxiety levels can be reduced.

5.4 Ethics and Privacy Protection

Given the global nature of epilepsy patients, data encryption standards (e.g., EU AI Act) should be established to build cross-cultural ethical consensus.

5.4.1 Privacy Protection

Encrypt storage of patient health data (e.g., seizure records, medication information) and biometric data (e.g., EEG) to comply with medical data regulations (e.g., HIPAA, GDPR). Studies indicate that EEG signals collected under identical stimuli can identify individuals with near 100% accuracy. Leaked biometric information from such stimuli can still identify individuals (Ruiz-Blondet et al., 2016). At the 2012 USENIX Security Symposium, Professor Ivan Martinovic from Oxford University introduced "brain spyware" that collects BCI data to steal information such as addresses, birthdates, credit card numbers, and acquaintances by analyzing users' visual stimulation responses (Martinovic et al., 2012). Hackers may alter BCI data to manipulate external devices for illegal purposes**Erro! A origem da referência não foi encontrada.** (Chen, 2025).

5.4.2 Liability Boundaries

Clearly define robots as auxiliary tools, not substitutes for professional medical advice.This fundamental distinction is critical to ensuring patient safety and maintaining the integrity of medical practice. To underscore this, explicit and prominent risk warnings must be incorporated into the operational protocols and user interfaces of these robotic systems. For instance, a warning such as “In the event of any discomfort or unwell symptoms, contact a doctor immediately” should be readily accessible and visible to users at all times (Schermer, 2009). Such warnings aim to prevent users from over - relying on the robotic systems and neglecting the necessity of professional medical diagnosis and intervention when necessary.

5.4.3 Cultural Sensitivity

Avoid misunderstandings due to cultural differences (e.g., epilepsy stigmatization in some regions) by designing inclusive dialogue logic. Cultural differences can significantly influence how health conditions are perceived, discussed, and addressed. For example, in some regions, epilepsy may be stigmatized due to traditional beliefs, myths, or lack of awareness about its true nature as a neurological disorder. Such stigmatization can affect patients' willingness to seek help, adhere to treatment, and discuss their condition openly. To address these challenges, it is crucial to design inclusive dialogue logic within healthcare technologies. This involves a thorough understanding of diverse cultural perspectives, values, and beliefs related to health and illness. By incorporating this understanding into the design of conversational interfaces, people can create more empathetic, appropriate, and effective interactions that respect cultural differences. By prioritizing cultural sensitivity in the design of healthcare technology dialogue logic, people can reduce the risk of misunderstandings, enhance patient trust, and improve the overall effectiveness of healthcare interactions, ultimately contributing to more equitable and accessible healthcare for diverse populations.

5.4.4 Fairness and Inclusiveness

Advocate for the inclusion of advanced devices (e.g., BCIs) in medical insurance to reduce the burden on low-income families. Expand rural coverage through telemedicine. Prevent predictive failures for specific groups (e.g., children or ethnic minorities) due to training data biases.

6 CONCLUSION

This paper systematically reviews the current state, applications, and future directions of human-computer interaction technologies for epilepsy patients. It examines challenges faced by epilepsy patients, including seizure unpredictability and limitations of traditional care. It also reviews the applications and limitations of BCIs, multimodal interaction technologies, AI, eye-tracking, and smart wearables in epilepsy monitoring, warning, and intervention. Furthermore, it proposes future research directions, including multimodal data integration, nano-BCI development, patient-centered design, and ethical and privacy protection. By integrating technology and humanistic concern, it aims to establish a comprehensive epilepsy management ecosystem covering monitoring, intervention, and feedback, providing full-cycle health management for patients.

BCIs, multimodal interaction technologies, and AI offer a transformative path from "passive control" to "active intervention" in epilepsy treatment, enhancing monitoring accuracy and intervention timeliness. However, clinical application challenges persist, including multimodal data fusion complexity, device long-term stability, real-time response delays, and ethical and privacy risks. Human-computer interaction technologies in epilepsy prediction still face challenges such as real-time response delays and data bias/fairness issues. Overcoming these requires technological innovations like more efficient algorithms and architectures, as well as social and policy support, including data sharing and fairness standard development. With advancements in brain science and AI, the future promises a safer, more precise, and inclusive epilepsy management system, achieving comprehensive support for "prevention-treatment-integration."

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