Toward Designing Motor Imagery-driven Hand Redirection in Virtual Reality for Upper Limb Rehabilitation

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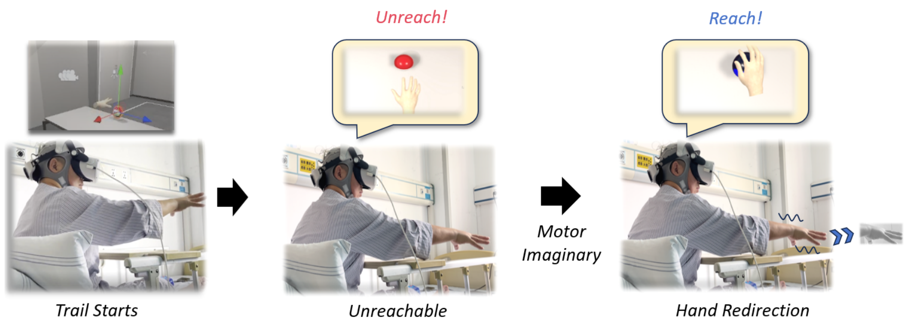

Fig. 1. MI-HR technique we designed in the work. (a) When the target refreshes in front of the participant, he puts effort into reaching the target; (b) When the participant approaches the target and finds it too far to reach, they need to use motor imagery (MI) to imagine the hand movement; (c) Intensive brain signal triggers the hand redirection (HR) on virtual hand to reach the target.

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ACM 2474-6567/2025/12-ART224
https://doi.org/10.1145/3770642

Motor-impaired patients often experience fatigue and low self-efficacy during rehabilitation training, which can hinder their compliance and the therapeutic effect. Hand redirection (HR) in virtual reality (VR) amplifies the visually perceived movement of users' virtual hand relative to the real hand, enabling users to tackle seemingly more challenging tasks, thereby boosting their motivation and exhibiting more effort in rehabilitation. However, prior HR techniques amplify users' hand movements without considering their engagement level, while active mental engagement is vital for stimulating neuroplasticity which enhances rehabilitation effects. To fully engage patients during rehabilitation, we proposed a Motor Imagery (MI)-driven HR technique, which only amplifies the virtual hand movement when users are fully engaged based on active brain signals. Our study with stroke patients revealed that, compared with Default-HR and No-HR, the MI-HR better engages patients' attention, while they perform better than No-HR in both HR conditions. We further discuss the design implications and potential applications of the system in broader rehabilitation scenarios.

CCS Concepts: • **Human-centered computing → Empirical studies in accessibility**; *Interaction paradigms*; *Virtual reality*.

Additional Key Words and Phrases: Motor impairments, Upper limb rehabilitation, Virtual hand redirection, Motor imagery

ACM Reference Format:
Peixuan Xiong, Jinhui Ouyang, Zhiqing Wu, Yukai Zhang, Xian Li, Chen Gong, Yuling Wang, and Mingming Fan. 2025. Toward Designing Motor Imagery-driven Hand Redirection in Virtual Reality for Upper Limb Rehabilitation. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 9, 4, Article 224 (December 2025), 27 pages. https://doi.org/10.1145/3770642

1 INTRODUCTION

Motor impairment is a common symptom after people survive from stroke, cerebral palsy, Parkinson's, injuries, motor neurone disease and muscle diseases. Stroke patients constitute the largest subgroup among people with motor impairments, and the prevalence of stroke has been increasing in recent years[1]. Stroke patients often lose partial or even complete control over their upper limbs, thereby losing the ability to live independently and perform activities of daily living, which significantly lowers their quality of life [2]. Upper limb impairment alters individuals' lifestyles; it impacts one's independence, restricting the ability to engage in work, social interactions, and activities of daily living [3, 4]. Upper limb rehabilitation is a common therapeutic process for stroke patients. With the proper treatment, poststroke patients may partially or fully regain control over their affected body parts, potentially aiding in restoring their motor function [5]. Numerous rehabilitation techniques for the upper limb have been introduced in medical settings, encompassing robot-assisted training [6, 7], sessions of motor training [8], constraint-induced movement therapy (CIMT) [9–12], physical therapy approaches [13–15], and VR/MR therapy [16–19]. In recent years, VR-based rehabilitation methods are becoming more popular due to their portability [20], comfort [21], and low cost [22, 23].

Recent research have investigated the use of VR hand redirectionas a promising technique for upper limb rehabilitation. It reveals that it enhances users' performance and motivation for rehabilitation by helping them achieve more tasks in exercises while maintaining *training effort*. For upper limb motor impaired users, high *success rate* in reaching targets can boost their motivation, and helping them at the end of each trails will enhance their endurance [24]. Research has found that engaging patients in VR with amplified, goal-directed movements that align with their anticipated actions can enhance their self-efficacy and lead to sustained improvements in motor skills [25]. A potential limitation of this technique is that it might not fully engage users' mental attention during training, as patients receive assistance regardless of their *engagement level*, while engagement is vital for effective rehabilitation. A high level of engagement is required for simulating neuroplasticity—the ability of unaffected brain areas to form new connections and compensate for lost functions—thus enhancing motor rehabilitation [26–29].

Motor Imagery (MI) is a brain-computer interface (BCI) paradigm which has been extensively validated and utilized for upper limb rehabilitation [30–35]. It involves converting neural activity signals of the brain into input signals for computers [36] or external devices [37] and allows patients with limb motor disorders to control external devices using brain signals [38]. This opens up new possibilities for rehabilitating stroke patients and aiding in the inducing of neuroplasticity in the brain [39]. As a means of control, MI has the potential to be applied in VR training to manipulate HR. By controlling virtual limb movements through motor imagery to complete tasks, patients can engage the motor cortex in actual movement while utilizing neural plasticity to facilitate the reconnection of brain neurons [40].

In this work, we proposed a MI-driven HR technique, which triggers virtual hand movement when it detects a sufficient mental effort from the patient. For example, the participant finds it too far to reach the target (Fig. 1 (b)), the patient should then start to imagine the hand movement. When the participant's intensive brain signals are detected as an MI, the HR will be triggered, and the virtual hand will then move toward the target, and the participant can reach (Fig. 1 (c)). This technique has the potential for patients to maintain a sufficiently high level of engagement and *training effort* while completing more tasks to enhance their motivation.

In this paper, we aim to explore the effectiveness of MI-HR in upper limb rehabilitation, particularly in improving patients' engagement, which reinforces the reconnection of brain neurons for a more successful recovery. Thus, our research question (RQ) is: **How might the MI-HR system affect *engagement level, training effort* and *success rate* in people with upper limb motor impairment during rehabilitation?** To answer this question, we first collected motor imagery data from stroke patients with upper limb motor impairment to setup the MI-HR system. Then we proposed a hand redirection system driven by motor imagery for upper limb rehabilitation with these data. We conducted an empirical user study to understand how the MI-HR system affects patients' *engagement level* and performance during rehabilitation. Results show that patients concentrate more on MI-HR condition rather than on the Default-HR condition, and perform better on Default-HR and MI-HR over No-HR. Moreover, almost all patients preferred MI-HR, as it allowed them to complete more tasks and lead to better brain recovery. We discussed the potential reasons for the preference and improved engagement, such as improved effort and perception of the MI-HR. In addition, we discuss the design implications derived from our findings and explore how the system could be extended to support other motor-impaired populations beyond stroke.

In summary, we made the following contributions:

- We introduced a MI-HR technique that adapts to the individual abilities of participants, enabling rehabilitation support for user with upper limb motor impairments only when it detects adequate mental effort
- We developed and trained an MI model by gathering data from users with motor impairments, advancing our understanding of how MI-based systems can be tailored to individual users.
- We conducted a comprehensive user study to assess the performance required by users with upper limb motor impairments during rehabilitation, investigating how MI-HR influences *engagement level* and performance throughout the process.

2 BACKGROUND AND RELATED WORK

2.1 Upper Limb Rehabilitation

Upper-limb motor impairment is a common symptom of stroke, cerebral palsy, Parkinson's, injuries, motor neurone disease and muscle diseases, significantly impacting patients' quality of life and everyday activities [41]. Upper limb rehabilitation helps patients regain independence in daily tasks, reduces their reliance on caregivers and healthcare professionals, and enhances their overall quality of life[42, 43].

The intensity of training [44, 45], task orientation[46, 47], patients' engagement [48, 49], and effort [50] play an important role for successful rehabilitation. To optimize these factors for rehabilitation, prior works have investigated a wide range of rehabilitation techniques involving technologies, such as CIMT therapy [9–12], biofeedback therapy [51], and robot-assisted therapy [52–55]. However, relentlessly pursuing these metrics can be counterproductive. For instance, a high-intensity treatment—requiring more than six hours of daily exercise, five days a week, and for a period longer than two weeks—may result in fatigue and diminished effort from patients

[56, 57]. At the same time, the lack of progress with fatigue feelings from long-term high-intensity training can undermine patients' confidence and motivation, leading to decreased neural engagement and diminished attention [58, 59].

To facilitate effective rehabilitation, we aim to propose a new method of rehabilitation to ensure sufficient rehabilitation intensity for the patients, while provides sufficient rehabilitation feedback to enhance the patients' motivation and effort. One promising technique is VR illusory interaction [60] by providing feedback on motor improvement in the virtual environment, patients would experience increased engagement and may be motivated to invest more effort in rehabilitation.

2.2 VR Hand Redirection (HR) for Rehabilitation

From the perspective of neurological rehabilitation, creating an illusion for patients that allows them to exceed the limited range of motion caused by paralysis may improve the motivation and effectiveness of rehabilitation therapy [61, 62]. Li et al. developed a stroke VR rehabilitation system by motivating the patients through subtle motion amplification on upper limb [63]. Tanaka et al. designed a hand remapping system for forearm rotation by rotating the angles of the upper limbs, which shows the potential to motivate patients' rehabilitation by creating a virtual scenario where the forearm rotates beyond the angle achievable by the real hand due to limitations caused by stroke-induced paralysis [60].

These methods applied in these studies can collectively be referred to as Hand Redirection (HR). HR in VR is a method widely used to augment movement in order to reduce fatigue [64, 65] and achieve pseudo-haptic feedback [66, 67]. Current common HR methods include fixing a displacement to the hand [68–70], scaling HR by a certain ratio [71–74], setting a redirection angle [75, 76], or achieving HR through a specific combination of different techniques [77].

Current research has shown that HR with fixed displacement and scaling movement, although helping patients to complete more tasks, may make the tasks feel too easy and not require much effort if HR is triggered at the beginning of the movement [24]. Triggering HR by hand moving closer to reaching the target can motivate patients to complete more tasks, requiring them to exert more effort and thereby increase their endurance [24]. However, this approach currently has a potential drawback, where the tasks are ultimately completed with assistance, similar to how a therapist helps a patient complete tasks in passive physical therapy. The design assists patients in completing their training by reducing the intensity of the exercise could potentially undermine engagement in the training process [78]. Sufficient evidence suggests that patient engagement plays a significant clinical role in rehabilitation [48, 49], because rehabilitation relies on neural plasticity to restore brain function [79]. This mechanism initiates activity-dependent neural rewiring during the recovery process after a stroke [80]. Through reconnection, the motor cortex can reactivate control over parts of the body, achieving substantial restoration of brain function [81].

In order to allow patients to maintain a high level of engagement to drive the restoration of brain function while utilizing HR to complete more tasks, we hope to find some integrated methods that encourage patients to engage more in order to drive VR HR.

2.3 Motor Imagery in Rehabilitation

Many existing rehabilitation programs rely on passive movement, where patients receive mechanical or manual assistance with little to no voluntary participation. For example, robotic arms may move patients' limbs without requiring effort or intention from the user [82, 83], or therapists may guide limbs manually during therapy sessions [84, 85]. While these approaches support early recovery, they lack the active cognitive involvement needed to drive long-term neuroplasticity. To address this, some systems have introduced alternative intent-based interfaces to promote engagement, such as eye gaze control to drive assistive devices [86, 87]. However, such methods engage users in task execution without activating their own motor intentions. As a result, it mainly stimulates visual and attention-related brain areas, promoting cognitive engagement but offering limited benefit for motor cortex activation, which is crucial for effective motor function recovery.

In contrast, motor imagery (MI) allows users to actively imagine movement, engaging the same sensorimotor areas of the brain as physical execution [88]. MI-based brain-computer interfaces (BCIs) can detect these neural patterns and have been used to trigger external devices like robotic arms [89] or control virtual environments [36].

Despite its potential benefits on motor function recovery, most prior MI-based systems assist users through external devices, making users feel that they are being helped rather than achieving their goals through their own efforts. Our proposed MI-HR system aims to bridge this gap by using MI to trigger gradual hand redirection in VR, helping users complete otherwise unreachable tasks without noticing it and increasing their active *training effort* and perceived control. In this way, users feel that they have accomplished more tasks through their own efforts, which motivates them to continue putting in more effort. MI-HR not only enhances patient engagement cognitively and physically, but also offers a middle ground between passive assistance and full motor control, making it particularly valuable in early-to-mid rehabilitation stages where patients have limited physical ability but preserved motor intention.

3 MOTOR IMAGERY-DRIVEN HAND REDIRECTION TECHNIQUE

In this section, we proposed a hand redirection system driven by motor imagery for upper limb rehabilitation. Based on this system, users can drive the redirection of the virtual hand through motor imagery, which can enhance their performance and engagement level in the rehabilitation tasks.

To capture the motor imagery signals triggered by patients, we first pre-trained on the EEG signals collected during tasks, distinguishing motor imagery signals from other signals (i.e. all EEG signals without motor imagery). For this purpose, we conducted an EEG data collection round with 10 stroke patients with upper limb rehabilitation.

3.1 Mechanism

To develop a system that leverages motor imagery-driven hand redirection for rehabilitation, we first designed the system architecture. In this system, users will first try to reach the target. If the users perceive the target as unreachable, they will then engage in motor imagery. Consequently, our system must first determine whether the user's hand has extended sufficiently far to evaluate the task difficulty, and subsequently assess whether the user's MI level meets the required threshold. Specifically, the system detects the distance between the user's hand position and their maximum reach—the farthest distance the user can reach, which is determined through an initial test at the beginning of the experiment. Only when the hand is sufficiently close to the maximum reach, the system then can confirm the user has exerted adequate physical effort to reach the target. Additionally, the system monitors the user's EEG signals after the hand approaches the maximum reach. The system triggers HR only when the EEG signal characteristics (e.g., power spectral density or frequency band features) match the user's pre-trained motor imagery patterns, indicating sufficient mental effort.

We define these two metrics—physical effort (based on hand position) and mental effort (based on EEG signals)—as thresholds. When both thresholds are simultaneously satisfied, the system automatically activates a hand redirection toward the target, assisting the user in successfully reaching it. These thresholds are personalized and determined by the user's individual capabilities, which are calibrated before the start of each formal experiment.

3.2 System Overview

The overview of our system is illustrated in Fig. 2. The system consists of three components: VR data processing, EEG data processing, and the neural network. The VR data processing branch uses data received from VR to

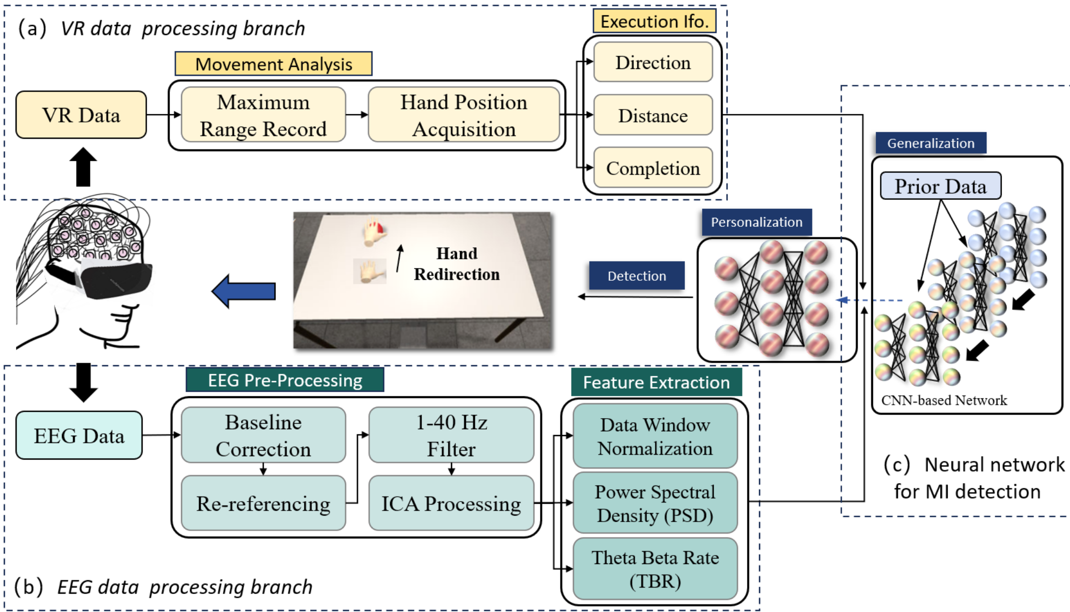

Fig. 2. The system architecture consists of three key components: (a) The VR data processing branch handles real-time hand-tracking, extracting users' maximum range and hand position for execution information. (b) The EEG data processing branch collects and pre-processes raw EEG signals, generating three types of features. (c) The proposed conventional neural network uses prior data for generalization and, after personalization with new participants' data, detects MI and activates HR.

analyze real-time physical performance and output the movement analysis results, including the direction, target position, completion, and hand position. The EEG data processing extracts useful features from real-time raw EEG data. Baseline correction, re-referencing, bandpass filtering, and independent component analysis (ICA) processing are conducted to pre-process the raw data. Subsequently, normalization is used to remove the effect of personalization-related EEG intensity; after that, power spectral density (PSD) and theta bate rate (TBR) are calculated as one of the features. The neural network is pre-trained with collected MI data and fine-tuned for individual participants to adapt with participant's efforts in moving their upper limbs. Beyond these components, we set a mental and physical activation threshold to control the execution time of HR, which influences the interactivity and user experience.

3.3 Real-time Processing

Before effectively interpreting the brain signals and invoking HR, our system first employs two parallel data processing branches to preprocess the real-time physical and neural data (VR hand tracking data and EEG data). VR data processing branch and EEG data processing branch are synchronized with Unix time. In the VR branch, the hand position in three-dimensional coordinates will be returned and recorded. Based on the position, our system will generate corresponding physical information for the personalization. In the EEG branch, a series of processes are conducted to filter EEG signals, remove noise, and extract useful features. In real-time interaction, raw EEG data is received in 1-second windows, and the buffer zone records 2-second data. To minimize the effect of artifacts and noise, 2-second data will be corrected by baseline and re-referenced to the average potential of the electrodes [90]. A motion-dependent effective frequency bandpass filter [91] of 4-40 Hz is applied to remove noise. Further, we use ICA to find and remove the major interfering noise to further reduce the influence of noise [92]. Subsequently, the pre-processed data is conveyed to the feature extraction module. Normalization is conducted in this module, which can cope with individual differences in a real-time EEG system [93]. Meanwhile, we calculated Welch Power Spectrum values using a Blackman-Harris window for theta (4-8Hz), alpha (8-13Hz), and beta (13-26Hz) bands [94]. Based on the calculation results, the feature extraction module outputs normalized data, PSD, and TBR for the next step. When a new participant engages, two types of features (VR and EEG) will be input into our neural network to fine-tune the classification performance and implement the personalization process.

3.4 Neural Network for EEG Signal Detection

The proposed classification framework includes two steps of training. The first step is pre-training with prior participants' data to generalize the neural network; the second step is fine-tuning with the data from a newly engaged participant to conduct personalization. Specifically, we first used the collected MI data to pre-train our framework, a proposed neural network cooperating with the meta-learning mechanism, and conduct the generalization. Then, each new participant engaged in our system is required to execute basic movements, and we collect a few data samples to fine-tune the proposed neural network to personalize the model.

3.4.1 CNN-based Neural Network. Conventional neural network (CNN) network is crucial for the development of the EEG application. For instance, Lawhern et.al proposed successful CNN variants to improve the classification accuracy of MI [95]. In recent years, CNN-based methods have shown more potential in real-time BCI systems and EEG applications [96]. By using the lightweight structure of CNN, it is possible to establish a BCI system with high classification accuracy and a fast reasoning time. Our proposed conventional neural network integrates three branches to fuse distinct feature types, enhancing classification accuracy [97]. The first input, window-normalized data, is processed through three blocks, each comprising a convolutional layer, a batch normalization, a ReLU activation, and a max pooling. The same structure is applied to the PSD feature, which has been shown to improve EEG signal classification. Additionally, the TBR feature, reflecting participants' attention and engagement, is included. All features are then flattened and fused in a fully connected layer. Finally, the fused features pass through two fully connected layers with ReLU activation to produce the classification results.

3.4.2 Meta-learning Mechanism for Fast Adaptation. CNN networks with randomly initialized parameters will take a long time and require a large dataset to train an accurate one. However, a long time of rehabilitation and large amounts of data collection are not acceptable for patients. To address these, we used a meta-learning method to pre-generalize our network and reduce the personalization needs of patients. Specifically, we use the ANIL meta-learning mechanism in [98], which is a lightweight transfer learning method to overcome cross-subject issues of EEG data. This method uses pre-collected data to pre-train the network and can generalize the network with a more adjustable parameter. After generalizing with the meta-learning mechanism, the proposed CNN network achieves time reduction for training around the same accuracy.

3.5 Data Collection

To achieve the function of recognizing and distinguishing MI from other EEG signals within the system, we conducted an EEG data collection session with 10 stroke patients undergoing upper limb rehabilitation.

3.5.1 Study Design. Participants were asked to complete a target-reaching task in VR, as illustrated in Fig. 3 (a). The target-reaching task is deliberately designed to support a wide range of upper limb movements while remaining intuitive and cognitively simple [99, 100]. Its simplicity allows it to be adapted for different patient conditions and cognitive states, making it a practical and sustainable option for rehabilitation. User feedback (Section 4.7.4) also suggests that participants found the interaction engaging and easy to follow, supporting the potential for user acceptance in repeated sessions. Before the experiment began, participants were informed that upon touching the target, it would change from red to blue, indicating the completion of the current task and the transition to the next. The target's position was continuously refreshed at varying distances and directions. To ensure participants understood the procedure, they were shown videos related to motor imagery before the experiment, emphasizing that if they found themselves unable to reach the target, they should perform motor imagery instead.

Additionally, we hypothesized that motor imagery is most likely to be triggered when the hand is approaching the target during the movement. Based on this assumption, we designated a specific point on the straight line from the starting position to the target, referred to as the "physical threshold." EEG signal collection began when the hand crossed this threshold and ended when the hand returned to this point after retracting.

If the task was not completed, we assumed that the participant followed the instructions to perform motor imagery, and the collected signals were considered characteristic of motor imagery. Conversely, if the task was completed, the participant was deemed not to require motor imagery, and the collected signals lacked motor imagery characteristics. These two types of signals were used to train a neural network, resulting in a system capable of determining whether EEG signals correspond to motor imagery. Data collection session costs 20 minutes for each participant.

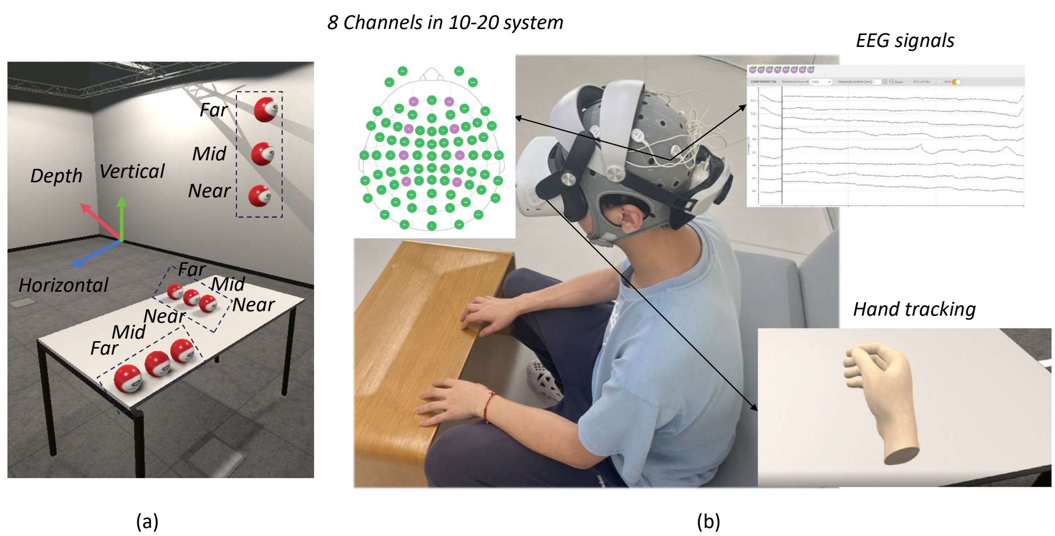

Fig. 3. The overall system architecture. (a) The targets refresh on different positions in three directions. (b) Participants wear the EEG headset and the VR headset, with EEG signals captured in real time and accurate hand tracking shown in VR. The 8 selected channels (Fp1, Fp2, T3, C3, C4, T4, O1, and O2) follow the 10-20 system paradigm, and is used to capture participants' EEG signals from the frontal, motor, and occipital lobe.

3.5.2 Apparatus. The study was carried out utilizing the Oculus Quest 2 headset (Fig 3 (b)), equipped with an Intel Core i7 CPU and an NVIDIA GeForce RTX 3070ti GPU. The VR rehabilitation application was designed and enabled using Unity. Through hand tracking, participants were able to observe the virtual depiction of their actual hands within the VR environment. Before wearing the VR headset, users must wear a Neuroelectrics EEG headset (Enobio 8 EEG system). This is a wireless dry electrode EEG system that is capable of performing real-time EEG data processing, including the handling of raw data and data filtering. The robustness of EEG signal processing against noise was ensured through the Enobio 8 system's ultra-low measurement noise (<1μV RMS), high input impedance (1GΩ), and exceptional common-mode rejection ratio (-115dB), which collectively suppress environmental and physiological interference. It consists of 8 Ag/AgCI dry EEG electrodes which were configured following the international 10-20 electrode configuration. Eight electrodes are situated at the positions of Fp1, Fp2, T3, C3, C4, T4, O1, and O2, as illustrated in Fig 4 (b). This setting of electrode position allows the combination of VR without hardware interference, meanwhile, enabling the collection of MI signals. Unix time is utilized to unify time expressions between two devices. Due to the necessity of wearing two devices, we always check before each experiment to ensure that the patient is comfortable with the equipment and that data collection is stable and effective.

Table 1. Participants' demographic information and their symptoms in data collection.

ID	age	Affect side	Motor impairments
1	36	Right	Moderate, able to move the arm against gravity (Grade 3 in MMT)
2	53	Right	Mild, able to move the arm against gravity and resistance (Grade 4 in MMT)
3	82	Left	Mild, able to move the arm against gravity and resistance (Grade 4 in MMT)
4	51	Left	Mild, able to move the arm against gravity and resistance (Grade 4 in MMT)
5	86	Right	Mild, able to move the arm against gravity and resistance (Grade 4 in MMT)
6	29	Left	Moderate, able to move the arm against gravity (Grade 3 in MMT)
7	54	Left	Mild, able to move the arm against gravity and resistance (Grade 4 in MMT)
8	14	Left	Moderate, able to move the arm against gravity (Grade 3 in MMT)
9	41	Left	Mild, able to move the arm without gravity and resistance (Grade 4 in MMT)
10	55	Right	Moderate, able to move the arm against gravity (Grade 3 in MMT)

3.5.3 Participants. We recruited 10 post-stroke patients (6 males, 4 females, $M = 50.1$, $SD = 22.1$) from the local hospital. None of the participants has experience with VR headsets, BCI, or MI, and they are all right-handed. Our recruitment criteria were based on the extensor and flexor muscles achieving grades 3-4 based on manual muscle testing (MMT) [101] on hands. Participants in these stages possess certain motor skills, yet there remains a gap compared to healthy individuals, necessitating continued hospital treatment. Additionally, we assessed the participants' mental state through the Minimum Mental State Examination (MMSE) [102]. All participants showed normal cognitive function, evidenced by their ability to express emotions and carry out simple arithmetic, getting grades higher than 22 in the MMSE. Ethical approval was secured from the ethics committees of both our affiliated institution and the hospital (2024ZSLYEC-071). Participants provided signed consent forms to participate and were compensated with a $10 shopping card. Detailed demographics are shown in Table 1.

3.6 Procedure

Preparation We conducted the data collection round in a quiet therapy room at a local hospital. We asked the patients sit at a suitable height table and place their affected hand comfortably on the tabletop in front of their chest. Before the experiment began, we first explained the purpose of our session through an informed consent form. After the patient signed it, we showed them a video of motor imagery, displaying the movements of both the virtual and real hands simultaneously, when the real hand reaches its limit, imagine the hand moving towards the target. We told them that this imagination could potentially make the virtual hand move and help them reach targets.

Warm-up We help the participants wear the EEG brain cap with VR headset and ensure they feel comfortable. To avoid training fatigue, we gave them one minute to familiarize themselves with the environment and tasks. Within the VR environment, participants discovered they were in a laboratory space, with an empty table in front of them and their impaired hands visibly resting on it. They were briefed that their objective was to reach a red target; a successful reach would be indicated by the target changing its color to black, upon which they should retract their hand to the initial position. We reiterated to the patients the importance of persisting in each trail to reach the target. If they couldn't physically touch it, they were encouraged to imagine their hand moving towards the target. After maintaining their effort for 3-4 seconds, we would remind them that they could retract their hand. No-HR were utilized during this warm-up phase.

MI data collection Participants were instructed to position their hands and bodies comfortably, as illustrated in Fig. 3 (b). Subsequently, they were asked to execute precise hand movements, including reaching, flexing, and performing horizontal abduction as extensively as they could across the x, y, and z axes, which denote depth, vertical, and horizontal directions, respectively (see Fig. 3 (a)). These exercises are frequently employed in rehabilitation practices [103]. The maximum reach distances in these three dimensions were recorded. Moving forward, a red target was generated in a location based on the initial and maximum position of the patient's hand, set at distances of 1 *(Near)*, 1.25 *(Mid)*, and 1.5 *(Far)* times their maximum range of motion along the x, y, and z axes (from Maximum to Initial Position). We established the concept of *Difficulty Levels* by defining various target distances. This approach allows us to differentiate between the *reach* and *unreach* states when patients attempt to reach the target. The refresh sequence of the targets starts with random appearances on the x-axis at distances of 1, 1.25, and 1.5, repeated twice for a total of six times, before switching to the y and z axes to follow the same refresh pattern. In HR conditions, for each of the three distances, participants completed one action under 1.25 times offset on the x-axis, then three reaching actions under 1.5 times offset. These parameters are referenced in prior work [24]. They obtained the gain parameters from formative study, users had difficulty detecting redirection at a gain of 1.25, while it became easier to be noticed at a gain of 1.5. Therefore, task difficulty in our study was also determined based on the gain parameter, ensuring a balance between perceptual subtlety and challenge, according to the literature. After the last refresh on the z-axis, it cycles back to the x-axis for another round. Thus, each participant completes 3 difficulty level × 2 repetitions × 3 directions × 2 repetitions = 36 trials in a single session. To collect a sufficient amount of data, and to prevent patients from experiencing fatigue due to excessive tasks, we set each session to approximately 20 minutes, which is similar to the duration of a typical rehabilitation treatment [104, 105]. We allowed patients to take a short break from the VR headset before beginning the other session.

After two sessions, we helped participants remove the headset and EEG cap. They completed a NASA-TLX questionnaire of 6 items, and answered questions about whether they perceived the effects of MI and how much they believed the system helped them in rehabilitation and recovery. The whole process took about 40 minutes in total.

3.7 Data Analysis and Model Training

We collected 720 trials of data in total with 10 participants. For each trial, we collected a set of VR hand-tracking data along with a corresponding set of EEG signal data. We only used the EEG data from the phase where the hand is about to extend to its maximum reach. We used these collected data to pre-realize the generalization of the MI-HR system. Compared with CNN without generalization, generalized CNN reduced the time to convergence average by 50%-70% and improved accuracy by 5%-15% when using the same amount of data to train. After generalization, the neural network gains an average classification accuracy of 76.81%, and the standard deviation is 15.91%. Result revealed strong individual differences in performance in different directions, which has been investigated in previous work, resulting in the accuracy variety of directions ranging from 70% to 92%. Previous studies revealed the request for personalization in EEG signal classification [98], which confirms that our design should add a personalization phase. In addition, as shown in Fig.4, spectrogram and TBR changing of one participant in horizontal tasks indicate a significant difference between reachable and unreachable tasks. We based on the difference to design the mental thresholds. The individualized mental thresholds were determined as the TBR values obtained through model fine-tuning, which effectively differentiated whether MI was triggered.

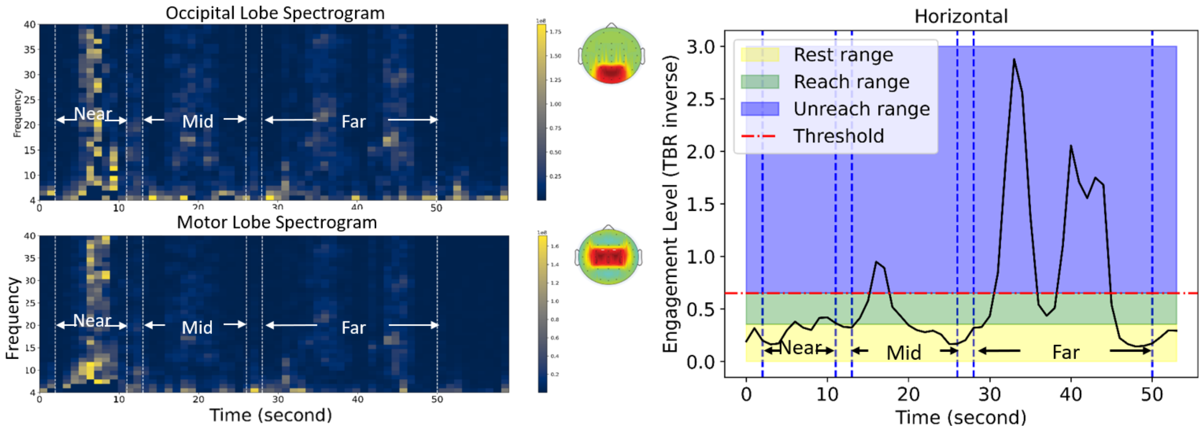

Fig. 4. One participant performed horizontal tasks, successfully reaching the target in the 'Near' task but failing in the 'Mid' and 'Far' tasks. EEG signals in the 4-40 Hz range were filtered for TBR and power spectral density analysis. The results suggest that in tasks where the target was unreachable, the participant's engagement level was elevated, and the band power remained stable and relatively strong.

4 USER STUDY

In this study, we investigate how MI-HR can affect people with upper limb motor impairment during rehabilitation and compare their *training effort* and *success rate* of tasks and *engagement level* under three conditions: *No-HR*, *Default-HR* and *MI-HR*. We conducted an empirical user study at the hospital with 10 participants.

4.1 Hand Redirection Techniques

To investigate how MI-HR affects rehabilitation in people with upper limb motor impairments, we compare three different HR techniques: No-HR, Default-HR, and MI-HR.

MI-HR is a HR technique introduced in this paper. This HR triggering condition is almost identical to the default-HR, requiring the hand to reach far enough to trigger a fixed displacement. However, after extending their hand far enough, participants also need to concentrate on performing MI. HR is only triggered when intensive brain signals are captured in real-time and their hands reach our set mental threshold. The mental threshold is selected through a pre-training method and is related to each individual's own performance. While there are differences between individuals, it remains consistent for each person in experiments using MI-HR.

During the interaction, we use two thresholds to implement our interaction scheme. First is the physical threshold, to detect patients' *training effort* exactly as Default-HR; second is the mental threshold, using the above mentioned method, to detect patients' *engagement level*. Once two thresholds approach at the same time, MI-HR activates. The physical threshold is selected from [24], and the mental threshold was determined by the user-fine-tuned EEG model.

Default-HR is a technique in which HR is driven by hand movement. As soon as the physical hand reaches a physical threshold close to its maximum reach, a gradually enlarging displacement is applied, extending the virtual hand toward the target until displacement reaches a preset constant. This technique has been investigated to enhance patients' motivation and endurance by inducing the needed workload while maintaining a high

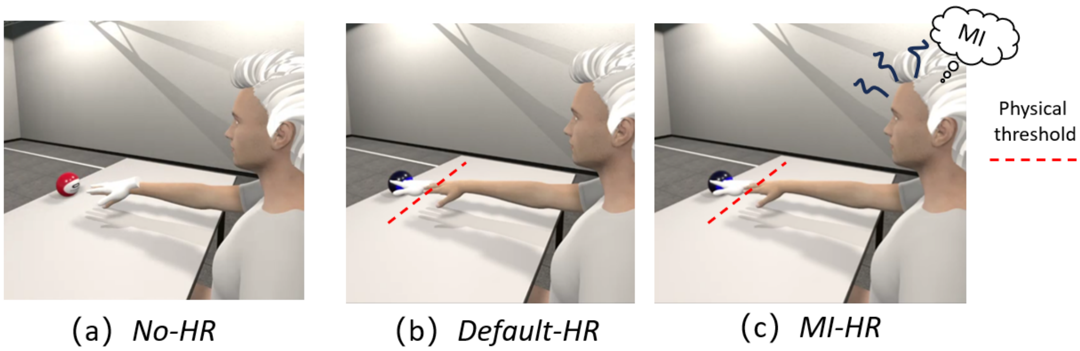

Fig. 5. Three hand redirection techniques in our study: (a) No-HR condition. The virtual hand moves exactly as the real hand. (b) Default-HR condition. As the physical hand reaches a threshold close to its maximum reach, a gradually enlarging offset is applied, extending the virtual hand toward the target until the offset reaches a preset constant displacement. (c) MI-HR. The physical threshold and displacement are the same as Default-HR, but the displacement only triggers when it meets the physical threshold with a strong MI signal. The avatar represent the real position of the participant and it is not shown during the rehabilitation. The participant can only see a virtual hand which is white in this figure.

success rate in accomplishing the tasks [24]. To make a comprehensive comparison in subsequent experiments, we chose the same parameters of the physical threshold as in previous work [24]. When the patient's hand position reaches 0.8 times the maximum reach, we consider that the patient has exerted sufficient effort to drive hand redirection.

No-HR is a baseline condition. The virtual hand moves exactly as the real hand.

4.2 Evaluation Metrics

In this study, we used the same apparatus and study setup as in the data collection round. We designed a within-subject study with 2 independent variables: 1)**HR technique**. It has three conditions: *No-HR*, *Default-HR*, and *MI-HR*. The settings for the HR techniques are adjusted to ensure that the deviation between the virtual and physical hands remains consistent across all redirection conditions when users fully extend their reach in the specified direction. In this study, No-HR is used as a baseline. To reduce fatigue during the study, we use No-HR as the warm-up session, and the protocol is the same as that for other conditions. During the warm-up session, we also collected personalized data from patients for fine-tuning to be used in training. The other two conditions were completed in a random order after the warm-up. 2) **Difficulty level** The target position is identical as in the data collection round, with three difficulty levels: Far, Mid, and Near.

Based on our research question, we primarily focus on three user metrics as dependent variables: 1) ***Engagement level***. To determine the participants' attention state throughout the study, the TBR based on the international 10-20 system was used. The TBR value was evaluated as people inattention index [106], and people show a high engagement when TBR is detected lower. The average TBR of healthy individuals is 2.08 ± 0.70, whereas poststroke patients show 5.39 ± 2.44 on average. It can be calculated using the following formula:

$$\mathrm{TBR} = \sum_{c=1}^{n} \frac{E\,(\mathrm{Theta})}{E\,(\mathrm{Beta})} \tag{1}$$

where c represents the channel index ranging from 1 to n ; $E(Theta)$ or $E(Beta)$ represents the energy of theta or beta band of each channel. The lower the TBR value is, the higher attention the participant is paid to the training. To intuitively demonstrate that the *engagement level* is positively correlated with the attention participants put in, We use 1/TBR instead of TBR to represent the *engagement level*.

2) ***Training effort***. We assessed one aspect of performance, specifically the *training effort*, during the training by calculating the average distance the hand moved in each trial. Our assumption is that the further the affected hand extends towards the target direction, the more effort is being invested in the training. To adjust for individual differences in capability among participants, we normalized the hand movement distance by dividing it by the maximum reach distance recorded for each participant during the preparatory phase.

3) ***Success Rate***. We utilize *success rate* as a dependent variable to examine the association between task difficulty [107] and the level of management. It compare users' task *success rate* under different difficulty levels and HR conditions. The *success rate* is another critical aspect of training performance, as the higher the participants' *success rate*, the greater their motivation and confidence to persist in more training sessions, fostering a positive cycle for rehabilitation [108].

4.3 Hypothesis

To investigate how different assistance strategies influence user *engagement level*, *training effort*, and *success rate* in tasks, we compared three HR conditions: Default-HR, MI-HR, and No-HR. In the Default-HR condition, users received immediate assistance, minimizing the effort required to complete a task. In contrast, the MI-HR and No-HR conditions required participants to initiate reaching on their own, without automatic support. When users could not reach the target (especially under No-HR and MI-HR conditions), they were instructed to perform MI to facilitate completion, which we expected to increase their attentional focus and *engagement level*.

Compared to the No-HR condition, other HR methods improved *success rate* by facilitating target reaching. Furthermore, in the Default-HR and MI-HR conditions, perceived assistance motivated users to exert greater physical effort. Increasing task difficulty was expected to further encourage the use of MI and promote greater physical effort. Based on these considerations, we propose the following hypotheses:

- H1: Both MI-HR and No-HR lead to higher *engagement level* than Default-HR.
- H2: Both MI-HR and Default-HR result in greater *training effort* than No-HR and the *success rate* metrics should not show a significant decrease between MI-HR and Dehault-HR.
- H3: Task difficulty modulates *engagement level* and *training effort*. Participants exhibit higher engagement and reach further when targets appear at farther positions.

To test these hypotheses, we conducted an empirical user study at the hospital and compared three HR techniques under different difficulty levels.

4.4 Participants

We recruited 10 other participants (8 males, 2 females, $M = 47.7$, $SD = 20.1$) from the local hospital. The recruiting criteria were the same as those for previous section. All participants were recruited based on consistent inclusion criteria, ensuring that their medical conditions were comparable. Participants were all diagnosed with the same condition and were in a stable phase of treatment. To minimize potential confounding factors, all medical interventions were kept consistent across participants, as managed by the attending physicians. Our study design was the only varying factor introduced during the intervention. Participants were compensated with local standards. Participants' demographic can refer to Table 2.

4.5 Procedure

We first gave a brief introduction of our study to participants. There were three sessions in this study, with the three redirection conditions. During the pre-experiment, we found that patients often became fatigued after two sessions even with a break session, especially since we required them to be mentally engaged throughout, and wearing a complex system that may cause discomfort. To prevent a significant decline in task performance due to fatigue and discomfort, we opted to shorten the experiment duration. Hence, We first conducted the No-HR

Table 2. Participants' demographic information and their symptoms in User Study.

ID	age	Affect side	Motor impairments
1	15	Right	Moderate, able to move the arm against gravity (Grade 3 in MMT)
2	26	Left	Mild, able to move the arm against gravity and resistance (Grade 4 in MMT)
3	67	Right	Mild, able to move the arm against gravity and resistance (Grade 4 in MMT)
4	32	Right	Moderate, able to move the arm against gravity (Grade 3 in MMT)
5	42	Right	Moderate, able to move the arm against gravity (Grade 3 in MMT)
6	73	Right	Mild, able to move the arm against gravity and resistance (Grade 4 in MMT)
7	38	Right	Moderate, able to move the arm against gravity and resistance (Grade 4 in MMT)
8	67	Right	Mild, able to move the arm against gravity and resistance (Grade 4 in MMT)
9	51	Right	Moderate, able to move the arm without gravity (Grade 3 in MMT)
10	66	Right	Mild, able to move the arm without gravity and resistance (Grade 4 in MMT)

condition. This also allows us to collect sufficient data to fit a personalized mental threshold for each participant. We counterbalance the order of the other sessions by Latin square. We did not disclose the techniques for each session to participants. We asked participants to fill in a questionnaire at the end of each session, and we asked questions regarding their perception of the session. After finishing all the sessions, we conducted a semi-structured interview. We first introduced the three techniques we applied in the study, then we let participants guess the order of the techniques and the reason for the answer, and then we disclosed the order of the techniques. We asked questions including their preference and suggestions of the techniques. The whole session takes around 25 minutes for training and 15 minutes for the interview.

4.6 Data Analysis

We obtained 108 trials for each participant in three sessions, and 10 participants achieved 1080 trials in total. We also collected EEG signal data during these training periods. The Shapiro-Wilk normality test was executed and revealed that the data from questionnaires did not follow a normal distribution. Still, data from travel distances of hands and TBR followed a normal distribution. Consequently, the Friedman test [109] was conducted to assess the difference between data in questionnaires and two-way repeated-measures ANOVA was conducted to assess the difference between data in *training effort* and *engagement level*. All interview data were recorded and automatically transcribed. Subsequently, two researchers independently coded the transcripts and conducted the inductive thematic analysis using the affinity diagramming approach [110].

4.7 Results

Next, we merge the participant data results with open coding interviews to explore the impact of MI-HR on people with motor impairments in terms of their *engagement level* and *training effort*.

4.7.1 *Engagement Level.*

Results show significant differences in different HR conditions ($F_{2,56} = 4.78$, $p = 0.012$, $\eta_p^2 = 0.146$) and difficulty level ($F_{2,56} = 7.75$, $p = 0.001$, $\eta_p^2 = 0.217$) in *engagement level*. No significant interaction was found between HR condition and difficulty level.

Pairwise comparisons were conducted as post-hoc tests following significant ANOVA results. Pairwise comparisons indicate significant differences between difficulty levels ($M_{Near} = 0.341 \pm 0.013$, $M_{Mid} = 0.398 \pm 0.019$, $M_{Far} = 0.409 \pm 0.020$). The Near level yielded significantly lower *engagement level* than both Mid ($t(56) = -2.88$, $p = 0.015$, $d = 0.77$) and Far ($t(56) = -3.76$, $p = 0.001$, $d = 1.01$), while the Far and Mid levels did not significantly differ ($t(56) = -0.88$, $p = 0.654$, $d = 0.24$).

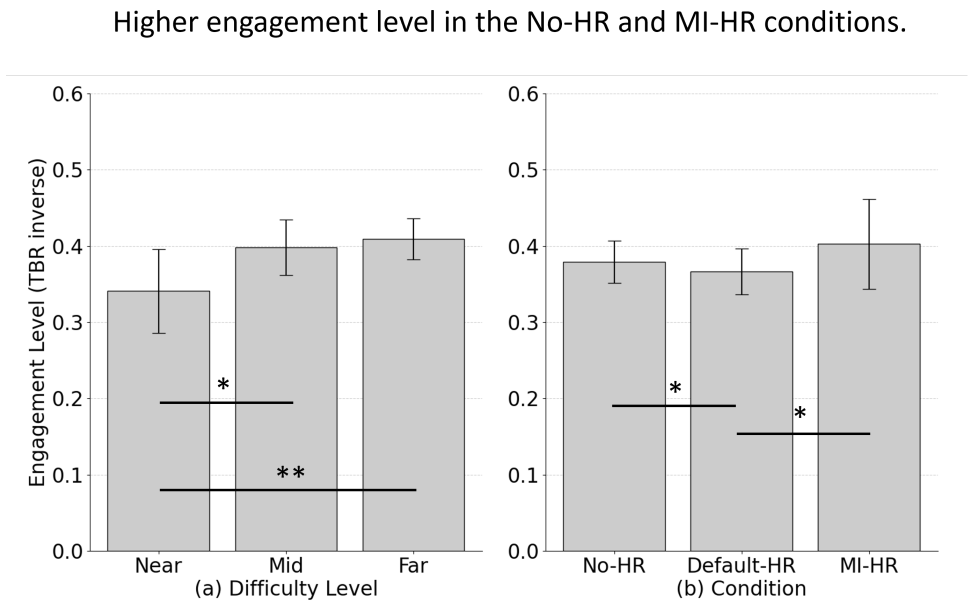

Fig. 6. Statistic results of participants' *engagement level*. (a)Participants show higher *engagement level* when tasks become hard. (b)Participants' *engagement level* under MI-HR and No-HR conditions showed no significant difference and were both higher than those under Default-HR. Statistical significant effects are marked ($* = p < .05, ** = p < .01, and *** = p < .001$). Error bars represent the standard error of the mean (SEM).

Among the three HR conditions, there were no significant differences between MI-HR ($M_{MI-HR} = 0.403 \pm 0.020$) and No-HR ($M_{No-HR} = 0.379 \pm 0.018$) in *engagement level* ($t(56) = -0.43$, $p = 0.905$, $d = 0.11$). *Engagement level* was significantly higher in MI-HR compared to Default-HR ($M_{Default-HR} = 0.366 \pm 0.016$; $t(56) = -2.86$, $p < 0.05$, $d = 0.77$), and significantly higher in No-HR compared to Default-HR as well ($t(56) = -2.44$, $p < 0.05$, $d = 0.65$). Results are shown in Fig 6.

4.7.2 Training Effort. Results show significant differences on HR conditions in *training effort* ($F_{2,56} = 18.36$, $p < 0.001$, $\eta_p^2 = 0.396$), and significant differences on difficulty level in *training effort* ($F_{2,56} = 96.42$, $p < 0.001$, $\eta_p^2 = 0.775$), with greater task difficulty leading to increased *training effort* by patients. No significant interaction effect was observed.

The pairwise comparison indicated significant differences between difficulty levels, with Near ($M_{Near} = 1.005 \pm 0.016$), Mid ($M_{Mid} = 1.224 \pm 0.023$), and Far ($M_{Far} = 1.33 \pm 0.031$) all differing significantly. The Near level yielded significantly lower *training effort* than both Mid ($t(56) = 9.31$, $p < 0.001$, $d = 2.49$) and Far ($t(56) = 13.58$, $p < 0.001$, $d = 3.62$), while the Mid level also resulted in significantly lower *training effort* than Far ($t(56) = 4.27$, $p < 0.001$, $d = 1.14$).

Results also indicate significant differences between HR conditions. There was a statistically significant difference in *training effort* between MI-HR ($M_{MI-HR} = 1.215 \pm 0.035$) and No-HR ($M_{No-HR} = 1.1 \pm 0.032$), $t(56) = 4.50$, $p < 0.001$, $d = 1.20$, as well as between Default-HR ($M_{Default-HR} = 1.248 \pm 0.036$) and No-HR, $t(56) = 5.77$, $p < 0.001$, $d = 1.54$. The difference between MI-HR and Default-HR was not statistically significant

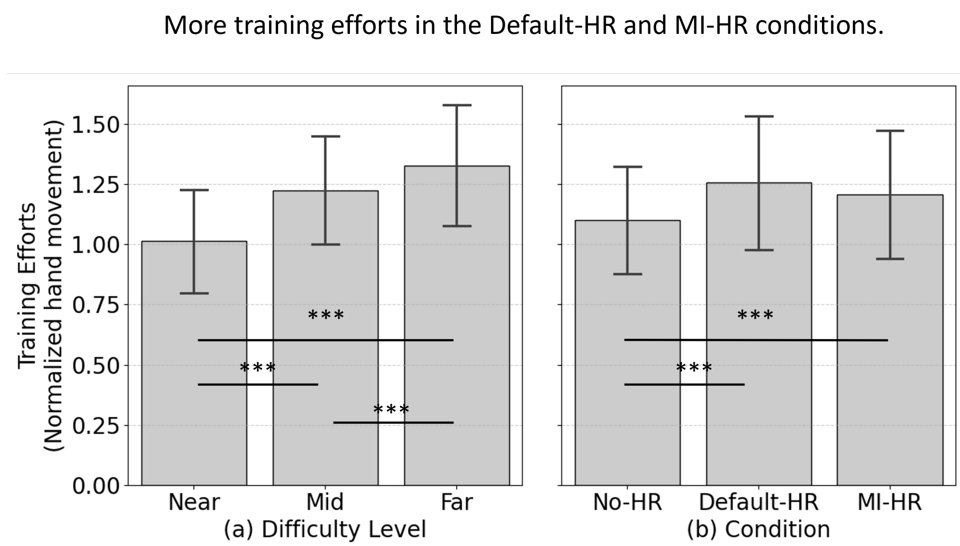

Fig. 7. Statistic results of *training effort*. (a)Participants show higher *training effort* when tasks become hard. (b)Participants' *training effort* under MI-HR and Default-HR conditions showed no significant difference and were both higher than those under No-HR. Statistical significant effects are marked ($* = p < .05, ** = p < .01, and *** = p < .001$). Error bars represent the standard error of the mean (SEM).

($t(56) = -1.27$, $p = 0.42$, $d = 0.34$), suggesting minimal practical difference between these two conditions. Results are shown in Fig 7.

4.7.3 Success Rate. *Success rate* was computed for each condition (session × distance) by calculating the percentage of successful trials out of repetitions. We conducted an aligned rank transformed ANOVA to examine the effects of HR conditions and difficulty level on task *success rate*. The model shows that both difficulty level ($F_{2,56} = 45.455, p < 0.001$, $\eta_p^2 = 0.619$) and HR condition ($F_{2,56} = 17.386, p < 0.001$, $\eta_p^2 = 0.383$) significantly affected the *success rate*. No interaction effect was found and thus was not included in further analysis.

Participants performed best at closer distances, with Near level ($M = 88.03\%\pm3.35\%$) significantly outperforming Mid level ($M = 72.53\% \pm 5.11\%$, $t(56) = 15.02$, $p < 0.001$, $d = 1.12$) and Far ($M = 43.93\% \pm 5.91\%$, $t(56) = 22.24$, $p < 0.001$, $d = 1.66$), and Mid level also significantly outperforming Far level ($t(56) = 7.23$, $p < 0.001$, $d = 0.54$). *Success rate* was also influenced by HR condition, with Default-HR ($M = 82.39\% \pm 3.56\%$) producing significantly higher success than No-HR ($M = 42.92\% \pm 7.15\%$, $t(56) = -5.85$, $p < 0.001$, $d = 0.78$), and MI-HR ($M = 74.18\% \pm 4.89\%$) also outperformed No-HR ($t(56) = 3.56$, $p < 0.001$, $d = 0.47$). There was no significant difference between MI-HR and Default-HR conditions ($t(56) = -2.29$, $p = 0.066$, $d = 0.30$). Results are shown in Fig 8.

4.7.4 Subjective Feedback. To compare the three systems with different conditions, our questionnaire questions include the user Experience Questionnaire (UEQ) and NASA-TLX. Questionnaire results show significant differences between different conditions on support reaching targets between three conditions ($p < 0.05$), mental efforts between MI-and other conditions ($p < 0.05$), and *training effort* between three conditions ($p < 0.05$). Participants reported they perceived exerting higher *training effort* in both MI-HR conditions and Default-HR

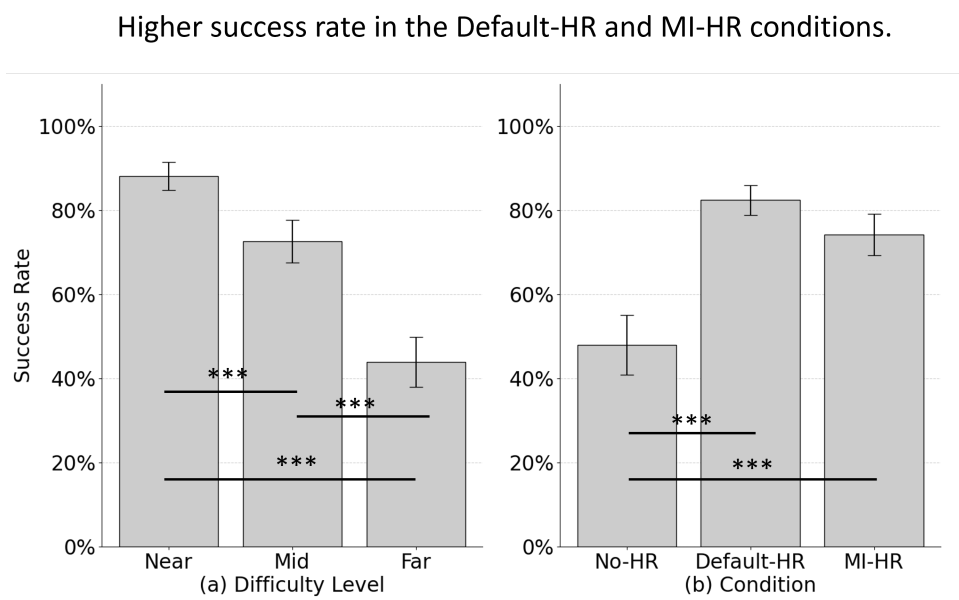

Fig. 8. Statistic results of the *success rate*. (a)Participants reach fewer targets in more difficult tasks. (b)Participants failed more in the No-HR condition. There are no significant differences between Default-HR and MI-HR. Statistical significant effects are marked ($* = p < .05, ** = p < .01, and *** = p < .001$). Error bars represent the standard error of the mean (SEM).

conditions, as they felt supported in both MI-HR conditions and Default-HR conditions, and they exerted the most mental effort into MI-HR conditions, Results are shown in Fig 9.

During the interview, almost all participants thought the MI-HR condition was more efficient. Most of them (N=8) could guess the order of all tasks correctly, as they discovered that using motor imagery in the MI-HR was effective. A few participants (P2, P4, P9) reported midway through the experiment that they found motor imagery to be effective.

For future rehabilitation solutions based on conditions they experienced, Most participants, except for P9, expressed a desire to use MI-HR in future rehabilitation for training benefits, while P9 stated to believe these approaches were still too premature. P9 reported that *"These rehabilitation approaches are too advanced for me; I would like to start with basic training first and consider this type of training in the future."* We believe this is related to the participant's recent initiation of upper limb rehabilitation. For other patients, the majority expressed a desire to combine Default-HR with MI-HR in their rehabilitation. For example, P4 reported *"I hope to use this approach to train and help with my brain recovery. But I also want to combine another method because I want to accomplish more tasks, which is also important for me."*

P2 only wishes to use MI-HR for rehabilitation training. This participant believes that Default-HR is similar to daily training, where the participant needs to sit down like a robot and start receiving treatment, and the participant cannot feel any real effectiveness. P2 reported that *"I think training must engage the brain. Even if using this approach is very tiring, I am willing to reduce the training volume and choose this approach."* P2 also showed us the belief of the No-HR condition is not friendly to patients. Due to the high difficulty and lack of assistance, patients may develop learned helplessness. Some other patients also mentioned that when trying to reach the target and finding it impossible to reach, they prefer to give up. This sometimes also happens in the MI-HR condition. This reminds us to be mindful of patients' psychological states while aiming to increase their engagement in rehabilitation by raising the difficulty level.

Some patients in this round also mentioned that the reach target training has improved joint mobility and made their hands more flexible compared to daily training, as they have to move in all directions during the exercise.

5 DISCUSSION AND DESIGN IMPLICATION

Building upon prior work on VR hand redirection for rehabilitation and MI, we designed an MI-HR system for upper limb rehabilitation. We collected motor imagery data from stroke patients and designed an MI-HR system to activate hand redirection in VR. We conducted a user study to understand how the MI-HR system affects patients' *engagement level* and *training effort* during upper limb rehabilitation. In summary, our findings show that in upper limb motor rehabilitation, MI-HR significantly improves participants' *engagement level* compared to Default-HR while maintaining the same high performance as observed in Default-HR. Based on the statistical test results and qualitative feedback above, we further summarized the key findings and implications.

5.1 Comparative Effects of HR Conditions on User *Engagement Level*, *Training Effort*, and *Success Rate*

MI-HR and No-HR achieve higher *engagement level* compared to Default-HR in engaging participants in rehabilitation. In the Default-HR condition, participants can easily complete tasks, and they reported that they hardly needed to focus in this condition. Therefore, participants exert the least amount of attention and engagement in the Default-HR condition. This result is similar to findings in passive training, where patients receiving assistance from devices or therapists during rehabilitation show significantly lower cognitive engagement than those participating in fully active rehabilitation [111, 112]. In contrast, similar to No-HR, MI-HR does not provide participants with assistance at the start, and hence participants paid higher focus in the MI-HR

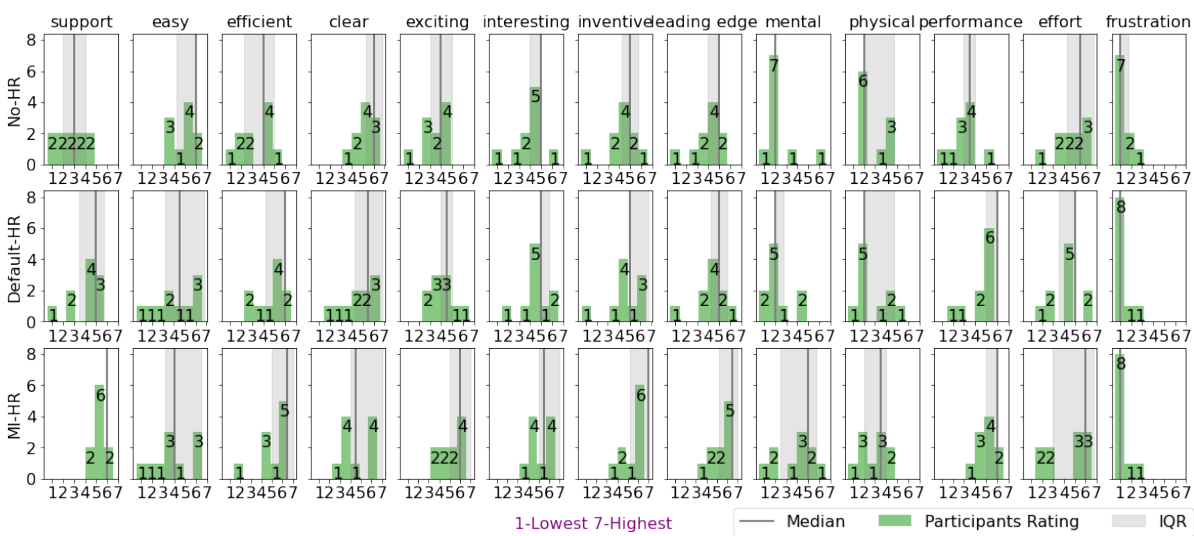

Fig. 9. Results of the questionnaire. Participants put more mental effort into MI-HR, and the MI-HR, and Default-HR support a lot in reaching targets. They believe they perform better in the MI-HR and Default-HR.

and No-HR, result in higher *engagement level* in these two conditions. Therefore, we fully accept **H1**: Both MI-HR and No-HR lead to higher *engagement level* than Default-HR.

MI-HR and Default-HR outperform No-HR in terms of *training effort* and *success rate*. Participants exerted significantly more effort in rehabilitation exercises with MI-HR and Default-HR compared to No-HR, as shown by the increased physical hand-moving distance. This is consistent with the findings of previous work [113, 114], which revealed that when rehabilitation tasks become overly challenging, some stroke patients demonstrate diminished motivation and difficulty sustaining effort, manifesting as reduced reaching distance during upper limb movements. In addition, both MI-HR and Default-HR resulted in higher *success rate* compared to No-HR, as the HR technique helped participants reach targets they could not achieve otherwise. Although the *success rate* between MI-HR and Default-HR did not show a significant difference, we observed that MI-HR participants had a slightly lower *success rate* despite exerting the same amount of effort. This may be due to the system sometimes failing to accurately detect participants' MI signals, or fatigue during the task weakening the EEG signal and preventing it from reaching the threshold required to trigger MI-HR [115–117]. Therefore, we fully accept **H2**: Both MI-HR and Default-HR result in greater *training effort* than No-HR, and the *success rate* metrics do not show a significant decrease between MI-HR and Default-HR.

Visually more difficult tasks lead to higher engagement and efforts. From our study, participants showed significantly higher *engagement level* when targets were refreshed at the "Far" position. Participants exhibit the lowest level of engagement when they are in the "Near" position, suggesting that users are more focused when the task appears to be more challenging. However, when the task seems impossible to complete, such as in the No-HR condition where targets refresh in the far position, users' *engagement level* is the same as when performing tasks of similar difficulty in the Default-HR condition.

Participants also reach farther when the targets refresh farther away from the participant's body among three conditions. Overall, patients are more willing to exert more effort to reach the target when the difficulty level is higher. Therefore, we accept **H3**: Task difficulty modulates **engagement level** and **training effort**. Participants exhibit higher engagement and reach further when targets appear at farther positions.

Based on the above results, we have drawn the following key conclusions: The MI-HR condition emerges as a better approach in rehabilitation by significantly improving engagement without compromising training effort or success rate compared to the Default-HR condition.

5.2 Design Implication

Dynamically adjust the difficulty based on the patient's condition. According to our discussion, future training programs can stimulate participants to put in more physical effort and mental engagement by increasing the task difficulty. However, overexerting the patients may backfire, leading to frustration and reduced training effectiveness or causing the system to fail in correctly identifying EEG signals. Several studies have shown that adjusting task difficulty or adjusting parameters for users' personalized learning can influence performance improvement [118–120]. This has also been studied in rehabilitation motivation theory, low motivation to engage in rehabilitation is associated with poor rehabilitation outcomes [121, 122]. Therefore, it is crucial to balance the task's dynamic difficulty appropriately. In future work, we can develop a real-time monitoring system with electromyogram (EMG) [123], accelerometers [124] or computer vision system [125] to track the patient's physical condition. The system also recognize the user's EEG signals in real time and adaptively adjusting the mental threshold based on their state. This ensures that participants receive timely and meaningful feedback when they exert sufficient effort in motor imagery but are unable to successfully trigger the MI. Such dynamic adjustment methods have already been widely applied in various VR rehabilitation scenarios, demonstrating improved patients' training performance compared to fixed training paradigms [126–130]. For example, Grimm et al. developed a closed-loop task difficulty adaptation system for rehabilitation to prevent slacking or frustration resulting from being over-challenged [131].

More features of the training system can be designed for longer rehabilitation periods. This study can also have implications for designing future long-term rehabilitation scenarios. We collect suggestions from our participants. First, participants prefer using MI to assist themselves in rehabilitation, since they thought it is essential to utilize the brain in rehabilitation. Training with excessive assistance makes them rehabilitate like a machine. Second, positive feedback is crucial as well. In addition to reaching the targets, other feedback can also be introduced. Given the lengthy rehabilitation period and the intensity of the training required after a stroke, patients desire to see immediate progress on their efforts. We also need to consider the patient's performance in activities of daily living (ADL) after training. If there is too much of a discrepancy between their *training effort* during training and post-training, it could also lead to frustration and self-doubt. Therefore, in future work, we can integrate Default-HR and MI-HR, and design a training system for long-term upper limb rehabilitation by providing tactile or auditory feedback. Previous research in rehabilitation and adaptive systems also explored dynamic or clinician-driven weighting strategies to combine multiple metrics into a composite score for therapy evaluation and personalization[132, 133]. We could incorporate periodic assessments by rehabilitation therapists to dynamically adjust the weighting of rehabilitation metrics and develop personalized training strategies with different HR techniques tailored to each patient's recovery needs.

Enhancing Remote Rehabilitation with VR and Serious Games. Since the participants recruited for our experiment had relatively high levels of muscle strength and their motor impairment symptoms were not particularly severe, the training process could be liberated from the confines of hospitalization and medical equipment. Our system can effectively motivate participants requiring home rehabilitation to maintain or restore muscle strength and encourage them to persist in their rehabilitation efforts [134, 135]. Moreover, there is an opportunity to integrate with serious games, using MI to accomplish upper limb motor tasks that are unattainable in conventional training, offering more training opportunities for the patients [136]. Through the immersive experience provided by VR, we can further enhance user engagement in training within serious games [137].

6 LIMITATION AND FUTURE WORK

While our results suggest the promise of MI-HR for upper limb rehabilitation, this work is limited in the following aspects. First, the data that we used to train the MI-HR system are obtained by extracting a fixed part from each trial. Such data is not ground truth because we cannot be sure that the patient is engaging in MI at every instance of "unreached." Since patients cannot express their imagination through thinking aloud while their brain activity is being monitored, in the future, we need to use other methods - such as providing a button for patients to press themselves or integrateing with EMG signals as a reference when they begin to imagine a movement to signify the start of MI . Second, the study did not incorporate a medical assessment. Each participant had a brief experience with the VR-based rehabilitation application, lasting less than an hour, which was insufficient for significant therapeutic results to be observed. Whether our research findings will change with long-term use remains unknown. Subsequent research could explore the extended impact of HR on therapeutic outcomes. Third, our findings only apply to patients with mild to moderate symptoms, as the study was conducted with patients with upper limb muscle strength levels between 3 and 4. Patients who cannot resist gravity may not be able to engage in HR, which is not in line with the approach explored in this study. Such a portable system may be better suited for patients with higher muscle strength levels who are gradually transitioning into the home rehabilitation phase. Fourth, the performance of our MI-HR system varies among individuals, and there are differences in accuracy. Although we have a fine-tuning phase, such adjustments may not be effective in a single instance over long-term rehabilitation. In future work, we aim to gather additional EEG signals for training and develop a highly accurate system that is universally adaptable, eliminating the need for a calibration session.

Fifth, our user study currently aims on stroke patients. The proposed system and adaptive control mechanism are designed to be generalizable to other motor-impaired populations. In future work, as long as the rehabilitation target involves neuroplasticity and upper-limb functional recovery, such as in cases of traumatic brain injury, cerebral palsy, or early-stage neurodegenerative disorders (e.g., Parkinson's disease), the same approach can be applicable. Last, some of the parameters used in our system design are based on previous work; we did not specifically design suitable parameter placements for this group. A more rational target placement might offer a more appropriate level of difficulty, further enhancing patient engagement. While our current evaluation considers each metric (engagement, training effort, and success rate) independently, the potential value of a composite evaluation framework that integrates these dimensions into an overall assessment could potentially assist the therapists in selecting the most appropriate HR mode based on patient-specific needs or rehabilitation stages in long-term rehabilitation.

7 CONCLUSION

In this paper, we design an MI-HR system for upper limb rehabilitation. Prior work has investigated triggering HR when patients approach the targets, and helping them achieve more tasks can enhance their motivation and endurance in rehabilitation while keeping them exhibiting enough *training effort*. This approach may decrease attention due to the ease of completing tasks. To further induce patients to focus their attention during training and increase engagement, we designed an MI-HR system for upper limb rehabilitation. A data collection round and a user study were conducted at a local hospital, with 20 participants with upper limb motor impairment. Our findings suggest that compared to Default-HR, MI-HR can significantly enhance users' *engagement level* while maintaining the same *training effort* and *success rate* in tasks, which can ensure patients put in sufficient *training effort* and enhance patients' motivation by enhancing success rate in their tasks. Most participants expressed interest in incorporating MI-HR with a higher success rate into future long-term VR rehabilitation programs. Our work is the first to integrate motor imagery with hand redirection, which can inspire future applications by combining these techniques in various scenarios.

Acknowledgment

This work is partially supported by Guangdong Provincial Key Lab of Integrated Communication, Sensing and Computation for Ubiquitous Internet of Things (No.2023B1212010007), Guangzhou-HKUST(GZ) Joint Funding Project (No. 2024A03J0617), and the Guangdong Provincial Clinical Research Center for Rehabilitation Medicine (No. 2023B110003). We would like to thank the participants for their time.

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