Report

A Human-Centered, Multi-Level Rehabilitation Training System Using EEG and Virtual Reality

Rebecca Metallo: *BSc in Mathematical and Computing Sciences for Artificial Intelligence*
Giulia Caffi: *MSc in Medicine and Surgery*

r.metallo@studenti.unisr.it
g.caffi@studenti.unisr.it

1 Project Proposal

1.1 Background and Motivation

Motor impairments caused by neurological conditions such as stroke, spinal cord injury, or neurodegenerative diseases often lead to a significant loss of autonomy and quality of life. Rehabilitation aims not only to restore motor function, but also to compensate for lost abilities and promote independence in daily activities. Achieving these goals requires long-term engagement, sustained motivation, and training pathways adaptable to individual motor capabilities. Motor rehabilitation is thus inherently demanding, relying on intensive repetition, consistency over time, and progressive task difficulty. Although clinically effective, traditional rehabilitation approaches are often perceived as exhausting, monotonous, and frustrating, particularly when progress is slow. These factors negatively impact motivation, adherence, and rehabilitation outcomes and thus from a clinical perspective, there is a strong need for rehabilitation environments that are safe, adaptable, and capable of supporting prolonged practice. Patients with complete or partial motor impairments frequently follow long and heterogeneous rehabilitation paths, requiring continuous adjustment of therapy while ensuring safety and sustained engagement.

1.1.1 Virtual Reality in Motor Rehabilitation

Virtual Reality (VR) has emerged as an effective tool in motor rehabilitation by providing safe, controlled environments for repetitive and task-oriented training [1, 2]. By transforming rehabilitation exercises into interactive and goal-driven experiences, VR enhances motivation and engagement. Moreover, through immersive environments and embodied avatars, it allows users to observe and practice movements without physical risk, which is particularly relevant for individuals with limited mobility. Clinical studies have also shown that VR-based rehabilitation can improve motor learning, therapy adherence, and neuroplasticity through repetitive, goal-directed tasks [1, 2].

1.1.2 EEG-Based Rehabilitation and Neuroplasticity

While VR effectively supports engagement and safe practice, it remains limited for individuals with absent or highly inconsistent motor output. In these cases, EEG-based systems offer a complementary solution by enabling access to motor intentions without requiring overt physical movement. EEG-based motor imagery paradigms activate motor-related cortical areas even in the absence of muscle activity, supporting functional reorganization and neuroplasticity. However, learning to generate stable and discriminable EEG patterns is cognitively demanding and often slow, resulting in increased cognitive load and frustration. In this context, feedback plays a crucial role by reinforcing motor learning, increasing awareness of neural activity, and enhancing the sense of agency. Feedback-driven brain–computer interface (BCI) training has shown promising results, particularly when embedded within structured and adaptive rehabilitation paradigms [3, 4, 6].

1.2 Key Idea

VR and EEG address complementary dimensions of motor rehabilitation. VR primarily supports engagement, repetition, and safe task execution through immersive and motivating environments, while EEG enables interaction without physical movement by providing direct access to motor intention. Their integration represents a powerful rehabilitation approach that combines clinical effectiveness with improved user experience.

This project proposes a human-centered, multi-level rehabilitation training system integrating EEG-based interaction with immersive VR environments. The system is designed to support motor recovery or functional compensation, promote autonomy, and sustain long-term engagement. By emphasizing adaptability, progressive task difficulty, and user-centered feedback, the proposed approach aims to reduce frustration, manage cognitive load, and foster consistent participation throughout the rehabilitation process.

1.3 Target Users

The proposed rehabilitation system is designed to support individuals with different degrees of motor impairment, addressing both assistive and rehabilitative needs. Users are characterized primarily based on their residual motor function, which directly influences training goals and interaction modalities.

User Type	*Motor Function*	*Interaction Modality*	*Primary Goal*
Complete Paralysis	No voluntary muscle activation	EEG-only	Assistive control of prosthesis/exoskeleton
Incomplete Paralysis	Residual motor function	EEG + EMG + IMU	Rehabilitation and improvement of motor execution

The system adapts to each user's abilities and rehabilitation needs.

1.4 Context of Use

The system is designed for deployment in both clinical and home-based settings, ensuring continuity of care across different phases of the rehabilitation process.

Clinical Setting. In clinical environments, rehabilitation sessions are conducted under the supervision of clinicians or therapists. Training follows structured rehabilitation protocols and can be integrated with existing assistive technologies, such as exoskeletons or prosthetic devices. This setting enables close monitoring of patient performance, fine-tuning of system parameters, and formal clinical evaluation of rehabilitation progress.

Home-Based Setting. In home-based scenarios, users engage in independent training routines according to personalized schedules defined during clinical assessment. The platform is designed to prioritize usability, minimal setup requirements, and robustness to environmental variability, allowing safe and effective training outside the clinical environment. Home-based use supports higher training frequency and sustained long-term adherence, complementing supervised clinical sessions.

1.5 Project Structure

The full project timeline, illustrating development phases and milestones, is available online and can be explored interactively at: Project Timeline on Figma.

2 User Analysis

From the early stages of the project, users have been actively involved in the design process, with their needs and limitations placed at the center of all technical and design decisions. The system architecture, interaction modalities, and training structure were defined through a user-centered approach, ensuring that usability, safety, and clinical relevance guided the development from the outset.

2.1 Personas

To better understand user needs and inform design decisions, a user analysis was conducted combining insights from the existing literature with a qualitative, user-centered investigation. The literature review highlighted recurring challenges in motor rehabilitation, including long-term adherence, cognitive load, frustration, and the need for adaptive and motivating training systems. Building on these findings, we designed a qualitative exploration aimed at capturing users' lived experiences, expectations, and attitudes toward rehabilitation and assistive technologies.

In order to construct realistic and representative user personas, we planned a semi-structured interview process. The goal of the interviews was to capture individual stories, goals, challenges, and motivations, as well as users' relationships with technology and rehabilitation practices. Semi-structured interviews were selected because they ensure coverage of key thematic areas while allowing participants the freedom to elaborate on aspects that are most relevant to their personal experiences. This flexibility is particularly important in rehabilitation contexts, where user needs and priorities can vary widely depending on clinical condition, personal background, and stage of recovery.

The question set served as the primary interview guide for exploring user experience dimensions and the gathered data will inform the creation of user archetypes (personas) for the system design. For access to the full questionnaire and personas, please refer to:`https://drive.google.com/drive/folders/1WhGmuBjgGEu2aOLDCS-uZRFO1LOqOzyJ?usp=share_link`

3 User Analysis Outcomes

Based on the insights derived from the literature review and the planned qualitative user analysis, a structured characterization of target users, goals, and needs was defined. Across both user groups, goals converge into three main areas:

- *Assistive Goal (Complete Paralysis):* Achieve reliable EEG-based control of a prosthetic or exoskeleton.
- *Rehabilitative Goal (Partial Movement):* Improve motor performance, coordination, and intention–execution consistency.
- *Psychological & Motivational Goal (Both Groups):* Ensure engaging tasks, sense of progress, reduced frustration, and meaningful feedback to maintain adherence and motivation.

3.1 Identified User Needs

From this analysis, the key user needs are:

- *Feedback:* Clear and immediate indication of intention recognition.
- *Progression:* Gradual increase in difficulty to avoid overload and frustration.
- *Motivation:* Engaging tasks reinforced by avatar embodiment to maintain adherence.
- *Adaptivity:* Interaction adapts to user capability (EEG-only vs EEG+EMG/IMU).
- *Cognitive Load:* Interfaces designed to minimize cognitive effort.
- *Tracking:* Monitoring improvements over time through the companion app.
- *Safety:* A controlled environment for practicing movements without risk.

3.2 Design Implications

User Need	Design Implication
Feedback	Visual feedback explicitly representing task state and classification outcome in real time.
Progression	Multi-level training with progressive difficulty, unlocked only when performance criteria are met.
Motivation	Game-like interaction design and avatar embodiment to enhance engagement and adherence.
Adaptivity	Dual interaction paths: EEG-only for users with complete paralysis; EEG + EMG + IMU for users with residual motor function.
Cognitive Load	Minimal and intuitive interface design aimed at reducing mental effort and preventing frustration.
Tracking	Access to session summaries and longitudinal performance data through a companion monitoring application.
Safety	Controlled virtual environments allowing repeated practice without physical risk.
Reliability (Assistive Use)	Assistive device integration enabled only after stable and reliable control has been demonstrated.

4 Scenario

To operationalize the identified user needs and design implications, a set of representative usage scenarios was defined. These scenarios translate abstract requirements into concrete, realistic situations, illustrating how different user types interact with the system in everyday rehabilitation contexts.
The scenarios serve as a design and validation tool, ensuring that interaction choices, feedback strategies, and system behavior remain aligned with user goals and capabilities.
Each scenario is accompanied by a corresponding sketch to support the design process. (Refer to `https://drive.google.com/drive/folders/1HQKjYswfecCAPMSDrHKJkNevv23PqnnK?usp=share_link`)

4.1 Scenario 1: Marco Rossi (Complete Paralysis)

"Regaining Control Through Mental Effort"

Marco, 32, sits at his desk at home beside his partner. After a **C5 spinal cord injury**, he has **no voluntary limb movement**, but his motivation to regain autonomy remains strong. Today, he begins a training session with the EEG-based system for users with complete paralysis.

He places the EEG cap and starts Level 1: Right Arm Movement vs Rest, based entirely on motor imagery. A visual cue signals the Rest phase, then the Preparation phase, and finally prompts him to imagine lifting his right arm. Although he cannot move physically, Marco vividly reconstructs the action mentally.

The avatar alternates between remaining still or performing the target movement, providing implicit feedback within the structured training context. Marco completes thirty repetitions, focusing while managing mental fatigue.
At the end of the ten-minute level, the system processes the EEG data and displays a performance summary. Marco sees that his accuracy approaches the threshold to unlock the next level, confirming that his effort yields measurable results.

Later, using the monitoring app (with the help of the partner), he reviews his session history and notes gradual improvement. For Marco, the training is more than exercise—it is a step toward controlling assistive devices and regaining independence.

4.2 Scenario 2: Anna Bianchi (Incomplete Paralysis)

"Rebuilding Strength with Support and Clarity"

Anna, 45, arrives at her rehabilitation center after work. She has **incomplete paralysis on her right side**, retaining partial movement but with inconsistent strength and coordination.

With her physiotherapist's help, Anna puts on the EEG cap and EMG sensors. Today's session follows a rehabilitative pathway, with the avatar demonstrating a simple reaching movement.
During each repetition, Anna observes the avatar, prepares herself, and attempts the movement while imagining it. She focuses on aligning intention with execution, with no scores or performance indicators to avoid distraction.

After thirty repetitions, the system processes EEG and EMG data. The summary shows improved intention–execution consistency compared to previous sessions. Anna and her therapist review the results through the monitoring app to plan future exercises.

Clear, distraction-free feedback helps Anna stay motivated. She feels supported, confident that her efforts contribute to long-term recovery.

4.3 Scenario 3: David Müller (Chronic Hemiparesis)

"A Gentle Approach for a Long Journey"

David, 60, lives alone in Zurich. After a stroke twenty years ago, he developed **chronic hemiparesis**. Having tried many rehabilitation programs with limited results, he approaches new technologies cautiously.

Today, David selects a simplified training session: a basic level focused on Rest vs Movement intention, with minimal visual complexity and instructions.

During the repetitions, he imagines lifting his affected arm while observing the avatar. The task is cognitively demanding, and he experiences mental fatigue. Unlike past programs, the system does not push him to continue.
After the session, the end-of-level summary shows a small but meaningful improvement in intention consistency.
Using the monitoring app, David compares today's session with previous ones. The gradual trend reassures him that his efforts matter. He later shares his experience with his support group, encouraging others facing similar challenges.

For David, the system offers not rapid recovery, but a respectful, sustainable way to stay engaged in rehabilitation.

5 User Journeys

User journeys were defined to detail the experience of interacting with the system across a complete training session, from preparation to session conclusion, capturing actions, thoughts, emotions, pain points, and opportunities.

5.1 User Journey — Marco Rossi (Complete Paralysis)

Goal	Regain sense of control using motor imagery.
Preparation	**Actions:** Positions himself at the desk; ensures the screen and environment are comfortable. **Thoughts:** "I want to focus and do my best today." **Emotions:** Hopeful, slightly anxious. **Pain Points:** Requires assistance for physical setup; mental fatigue even before starting. **Opportunities:** Consistent session routine; calming visual environment to reduce anxiety.

Setup	**Actions:** Places the EEG headset with assistance and follows guided setup instructions. **Thoughts:** "I hope the system captures my intentions clearly." **Emotions:** Focused, cautious. **Pain Points:** EEG setup feels technical and time-consuming. **Opportunities:** Step-by-step guidance; confirmation when setup is complete.
Training Interaction	**Actions:** Performs motor imagery of right arm movement across 30 repetitions, following Rest–Preparation–Movement cues. **Thoughts:** "I need to stay concentrated and consistent." **Emotions:** Mentally engaged, sometimes fatigued. **Pain Points:** Uncertainty about performance during the session. **Opportunities:** Minimal, non-distracting interface; predictable structure to support sustained focus.
End-of-Level Feedback	**Actions:** Reviews the performance summary displayed after the level. **Thoughts:** "I can see whether my effort is paying off." **Emotions:** Reassured, motivated. **Pain Points:** Fear of slow progress or plateauing. **Opportunities:** Clear accuracy values; comparison with previous sessions.
Session Conclusion	**Actions:** Checks progress trends on the monitoring app. **Thoughts:** "I am gradually getting closer to independence." **Emotions:** Pride, cautious optimism. **Pain Points:** Long-term uncertainty about outcomes. **Opportunities:** Goal-setting features; clinician feedback through the app.

5.2 User Journey — Anna Bianchi (Incomplete Paralysis, Rehab)

Goal	Improve coordination and regain confidence.
Preparation	**Actions:** Arrives at the rehabilitation center after work. **Thoughts:** "I'm tired, but I want to keep improving." **Emotions:** Fatigued, determined. **Pain Points:** Time constraints; emotional exhaustion. **Opportunities:** Predictable session length; reassurance that effort matters.
Setup	**Actions:** Wears EEG and EMG/IMU sensors with assistance from the therapist. **Thoughts:** "Will my movement be stable today?" **Emotions:** Curious, slightly insecure. **Pain Points:** Sensor discomfort; fear of inconsistent performance. **Opportunities:** Comfort-oriented sensor placement; therapist support.
Training Interaction	**Actions:** Attempts the instructed movement while imagining it, following the avatar's cues. **Thoughts:** "I need to coordinate what I think and what I do." **Emotions:** Engaged, occasionally discouraged. **Pain Points:** Variability in physical execution. **Opportunities:** Clear task cues; absence of mid-session judgment reduces pressure.
End-of-Level Feedback	**Actions:** Reviews a combined summary of intention consistency and execution quality. **Thoughts:** "Now I understand what is improving." **Emotions:** Reassured, encouraged. **Pain Points:** Improvements may feel slow or subtle. **Opportunities:** Visualization of small gains; clinician explanation of results.
Session Conclusion	**Actions:** Checks weekly progress trends with the therapist on the monitoring app. **Thoughts:** "Even small steps forward count." **Emotions:** Motivated, more confident. **Pain Points:** Managing cumulative fatigue. **Opportunities:** Adaptive scheduling; personalized rehabilitation goals.

5.3 User Journey — David Muller (Chronic Condition, Low Motivation)

Goal	Maintain minimal function without overwhelm.
Preparation	**Actions:** Decides to attempt a short and simplified session at home. **Thoughts:** "I'll try, but I don't want to feel overwhelmed." **Emotions:** Hesitant, reserved. **Pain Points:** Low intrinsic motivation. **Opportunities:** Optional short sessions; reassurance of flexibility.
Setup	**Actions:** Launches the simplified interface with minimal visual elements. **Thoughts:** "I hope this stays simple." **Emotions:** Cautiously willing. **Pain Points:** Fear of complex or demanding interfaces. **Opportunities:** Minimalist design; large, clear buttons.
Training Interaction	**Actions:** Performs slow motor imagery during the guided phases. **Thoughts:** "I'm doing what I can." **Emotions:** Calm, occasionally uncertain. **Pain Points:** Mental fatigue appears quickly. **Opportunities:** Low cognitive load; no pressure to perform perfectly.
End-of-Level Feedback	**Actions:** Reviews a simplified performance summary. **Thoughts:** "This feels manageable." **Emotions:** Slight encouragement. **Pain Points:** Very gradual progress. **Opportunities:** Highlighting consistency rather than absolute performance.
Session Conclusion	**Actions:** Ends the session early if needed and saves progress. **Thoughts:** "At least I showed up today." **Emotions:** Quiet satisfaction. **Pain Points:** Risk of disengagement over time. **Opportunities:** Gentle motivational messages; weekly activity reminders.

5.4 Clinical–Longitudinal Pathway

While scenarios and user journeys describe the user experience within a single training session, rehabilitation unfolds over a longer time horizon and involves clinical decision-making, supervision, and adaptation.
To capture this dimension, a clinical–longitudinal pathway was defined, describing how the system is used across multiple sessions and how clinicians and patients jointly guide progression throughout the rehabilitation protocol.
(Please refer to `https://drive.google.com/drive/folders/13b7i-A3PGEbWwTO9C5RWC_84ak1015nF?usp=share_link`)

6 System Architecture

The proposed rehabilitation system is composed of modular hardware and software components designed to support both EEG-only assistive interaction and multimodal rehabilitation pathways. The architecture enables reliable biosignal acquisition, real-time processing, immersive VR-based interaction, and longitudinal monitoring, while remaining adaptable to different user capabilities and contexts of use.

6.1 Hardware Components

- **EEG Cap with Gel Electrodes**
  Non-invasive EEG system used to acquire brain activity related to motor imagery or attempted movement. Gel electrodes ensure stable signal quality during both clinical and home-based sessions.
- **EMG and IMU Sensors (Optional)**
  Peripheral sensors used for users with residual motor function. EMG captures muscle activation patterns, while IMU sensors provide information on limb movement and orientation. These sensors enable multimodal interaction and support rehabilitation-oriented training.
- **Acquisition Computer**
  A computer dedicated to biosignal acquisition, responsible for receiving raw data streams from EEG (and optional EMG/IMU) devices and forwarding them for synchronization and processing.

- **Processing Computer**
  A separate machine responsible for real-time signal processing, feature extraction, decoding, and communication with the VR environment. This separation improves system robustness and scalability.
- **VR Headset**
  Immersive display device used to present the virtual training environment and embodied avatar feedback. The VR headset supports engagement, presence, and intuitive visual feedback during training.

6.2 Software Components

- **EEG Acquisition Software**
  Software provided by the EEG hardware manufacturer, responsible for recording raw EEG signals and managing device configuration.
- **Lab Streaming Layer (LSL)**
  Middleware used for real-time stream synchronization across multiple data sources (EEG, EMG, IMU, task events). LSL ensures precise temporal alignment between biosignals and interaction events.
- **Python-Based Processing Pipeline**
  A modular pipeline implemented in Python for signal preprocessing, feature extraction, and machine learning–based decoding of motor intention. The pipeline supports both calibration and real-time inference modes.
- **Unity-Based Avatar Environment**
  A Unity application responsible for rendering the virtual environment, avatar embodiment, task cues, and visual feedback. Decoding outputs from the processing pipeline are mapped to avatar behavior and task state updates.
- **Smartphone Application (Companion App)**
  A mobile application used for session review and longitudinal monitoring. The app provides access to session summaries, progress trends, and adherence metrics for users, caregivers, and clinicians.

7 Task Analysis

To systematically describe user interaction with the proposed system, a task analysis was conducted focusing on the execution of a structured motor-intention training session.

7.1 Task Definition and Scope

The system is designed to support users in performing a structured motor-intention training session within a controlled human–machine interface. Each training level lasts approximately 20 minutes and consists of 60 repetitions, divided into two consecutive phases of 30 repetitions each. Each repetition is composed of three sequential phases—Rest, Preparation, and Movement/Motor Imagery—and is accompanied by a virtual avatar.

During the first phase, the avatar performs the movement continuously and independently of the user's neural activity, serving as a visual guide without providing performance-related feedback. EEG signals (and, when applicable, EMG/IMU data) are recorded offline during this phase for subsequent classifier training.

At the transition between the two phases, the system processes the recorded data and trains a personalized classifier.

During the second phase, real-time classification and feedback are enabled. The avatar executes the movement only when the classifier prediction correctly matches the user's intended action, providing contingent visual feedback based on model output.

At the end of the level, the system displays a performance summary based on real-time classification accuracy during the feedback phase. Level progression is determined by a predefined accuracy threshold:

- Accuracy $\geq 85\%$: the next level is unlocked.
- Accuracy $< 85\%$: the user is encouraged to repeat the level with supportive and non-judgmental feedback.

The choice of this threshold is motivated by evidence from the BCI literature, which suggests that systems achieving classification accuracies below approximately 70% are generally considered unreliable or unacceptable for practical use, whereas accuracies above 75% are commonly regarded as indicative of successful and usable BCI systems.[4]

Based on these findings, an accuracy threshold of 85% was selected as a conservative and design-driven criterion to ensure stable intention decoding before task progression, reduce the likelihood of inconsistent feedback , and support user trust and motivation in the context [7, 8].

7.2 Hierarchical Task Analysis (HTA)

1. Complete a training level
    (a) Prepare the environment
        i. Position oneself in a stable and comfortable posture
        ii. Adjust the display and seating position
        iii. Reduce external distractions
    (b) Set up sensing devices
        i. Wear EEG headset
        ii. Attach EMG/IMU sensors (if applicable)
        iii. Verify signal quality and impedance
    (c) Perform Phase 1: Offline training (30 repetitions)
        i. Rest
        ii. Preparation
        iii. Movement / Motor imagery
        iv. Observe continuously moving avatar (no feedback)
        v. Transition to next repetition
    (d) Train personalized classifier
        i. Process recorded EEG (and EMG/IMU) data
        ii. Train subject-specific classifier
    (e) Perform Phase 2: Real-time feedback training (30 repetitions)
        i. Rest
        ii. Preparation
        iii. Movement / Motor imagery
        iv. Receive contingent visual feedback based on classifier output
        v. Avatar moves only if prediction is correct
        vi. Transition to next repetition(f) Generate performance summary
    (f) Generate performance summary
        i. Compute real-time classification accuracy
        ii. Aggregate performance metrics
        iii. Display level summary
    (g) Evaluate level completion
        - Accuracy $\geq$85% $\rightarrow$unlock next level
        - Accuracy $<$ 85% $\rightarrow$recommend level repetition with supportive feedback
    (h) Conclude session
        i. Save performance metrics and session data
        ii. Rest or start a new training session
    (i) Review results (optional)
        i. Access monitoring application
        ii. Review and compare session outcomes
        iii. Share results with clinician or caregiver

To complement the hierarchical task decomposition, the following table summarizes the cognitive, physical, and perceptual demands associated with each task phase.

Task Phase	Cognitive Demand	Physical Demand	Perceptual Demand
Setup	Medium	Low to medium	High (device placement and UI alignment)
Rest	Low	Low	Medium (monitoring cues)
Preparation	Medium	Low	Medium
Movement / Motor Imagery	High	Medium for incomplete paralysis; low for others	Low
Feedback Interpretation	Medium	Low	Medium
End-of-Session Summary	Low	Low	Medium
App-Based Review	Low	Low	Medium

7.3 Design Implications

- **Structured, Repetitive Training**
  Training is organized into short, repeated trials with a predictable phase structure (Rest–Preparation–Movement), supporting engagement while limiting cognitive fatigue.
- **Implicit Feedback During Execution**
  During the real-time phase, the avatar provides implicit feedback by executing the movement only when the decoded intention is correct, allowing continuous perception of system responsiveness without explicit performance indicators.
- **Deferred Performance Summary and Progression**
  Overall performance is summarized at the end of each level, and progression to higher levels is enabled only when predefined reliability criteria (e.g., $\geq 85\%$ accuracy) are met.
- **Fatigue and Pause Management**
  Optional pauses are supported within or between training phases to accommodate mental fatigue, ensuring safety and long-term adherence.
- **Minimal and Adaptive Interface**
  Interface complexity is adapted to user characteristics and interaction modality to minimize cognitive load and reduce frustration.
- **Longitudinal Monitoring**
  A companion application supports review of trends and micro-improvements over time, facilitating motivation and clinical decision-making.

8 Level Design

The training program is organized into standardized, progressive levels with fixed duration and consistent structure. This design promotes familiarity across sessions, reduces uncertainty, and supports learning through repetition. Task complexity and control requirements increase gradually, and progression to higher levels is enabled only after stable and reliable performance is achieved, ensuring robust intention decoding before increasing task demands.

While the overall level structure is shared, two training pathways are defined to address different user profiles and rehabilitation goals.

Assistive Training Pathway (EEG-only).

Designed for users with complete paralysis, this pathway focuses on developing reliable EEG-based motor intention decoding for assistive control. Task complexity progresses from simple binary classifications to more fine-grained motor imagery discrimination, including:

- Right arm movement vs rest
- Right arm vs left arm movement
- Upper limb vs lower limb movement
- Different movements of the same limb (e.g., wrist flexion vs elbow extension)

Rehabilitative Training Pathway (EEG + EMG/IMU).

Designed for users with residual motor function, this pathway emphasizes rehabilitation through tasks combining motor imagery with partial physical execution. Training targets intention–execution coherence, movement consistency, and functional recovery through:

- Assisted reaching movements of the impaired upper limb
- Repeated wrist or elbow flexion and extension
- Bilateral arm movements for coordination training

- Functional movement patterns such as reach-and-grasp

Across both pathways, the adaptive multi-level structure aligns task difficulty with individual capabilities, supporting safe progression, long-term engagement, and clinically meaningful outcomes.

9 EEG Analysis Pipeline: Offline Training vs Real-Time Inference

EEG data analysis is implemented in Python using the MNE library for EEG signal processing [5]. The processing pipeline is structured into two complementary phases: an offline training phase used for model calibration and a real-time inference phase used during interactive training with feedback.

Phase 1 – Offline Training (Model Calibration)

During the first phase of each training level, EEG data are recorded without real-time feedback and used to train a subject-specific classifier.

- Raw data storage: Continuous EEG signals are saved to raw files to ensure reproducibility and allow offline inspection.
- Channel quality control: Bad channels are identified and removed based on signal quality.
- Band-pass filtering: Signals are filtered to retain task-relevant frequency components associated with motor imagery.
- Epoching: Continuous data are segmented into task-related epochs corresponding to Rest, Preparation, and Movement/Motor Imagery phases.
- Feature extraction: Discriminative spatial features are extracted using Common Spatial Patterns (CSP).
- Model training: Data are split into training, validation, and test sets, and a Linear Discriminant Analysis (LDA) classifier is trained and validated.

This phase produces a personalized model optimized for the user's neural patterns.

Phase 2 – Real-Time Inference (Feedback-Based Interaction)

In the second phase, the trained model is deployed for real-time decoding and feedback.

- Real-time preprocessing: Incoming EEG data are filtered and epoched online using the same parameters defined during offline training.
- Feature projection: CSP filters learned in Phase 1 are applied to incoming data to extract features in real time.
- Intention decoding: The trained LDA classifier estimates the user's motor intention on each trial.
- Contingent feedback: Decoding outputs are mapped to avatar behavior, enabling implicit feedback through movement execution only when predictions are correct.
- Performance logging: Classification outcomes are logged to compute end-of-level performance summaries and support longitudinal monitoring.

10 Prototypes (Lo-Fi, Figma, Unity, EEG)

The prototyping activity supported the iterative development of the proposed system and served as a validation step for the design decisions discussed in previous sections. Given the complexity of the platform, detailed functional specifications for both the training system and the monitoring application are documented separately and are not repeated here (see project repository: `https://drive.google.com/drive/folders/1RzizyKOmwNo-ifvcXfsu2kROJefakN9d`).

Because the system includes both a real-time training component and a longitudinal monitoring component, the prototyping process was organized into two complementary streams:

1. Training system prototypes, focusing on game interaction, EEG integration, and avatar-based feedback.
2. Monitoring application prototypes, focusing on longitudinal visualization, accessibility, and clinician–patient interaction.

10.1 Training System Prototype — Game Interface (EEG + Python)

The training system prototype focuses on real-time interaction and motor-intention learning. A functional end-to-end prototype was implemented to validate the feasibility of the complete pipeline, from EEG signal acquisition to visual feedback.

The game interface and training flow were implemented using a Python-based game development library (pygame). This choice enabled rapid prototyping and iterative refinement of timing, task phases (Rest, Preparation, Movement), and interaction logic. The graphical interface runs on a dedicated computer connected via Ethernet to the EEG recording system. Inter-device communication is handled through the Lab Streaming Layer (LSL), ensuring precise temporal synchronization between signal acquisition, classification, and visual feedback.

Design principles guiding the game interface include:

- simplicity and visual clarity,
- minimal on-screen elements,
- clearly defined task phases,
- adaptive pauses to accommodate user fatigue,
- feedback integrated coherently with the training phase.

A demo of the training system, including both the initial and refined versions developed after user feedback, as well as the game source code, is available online at:
(`https://drive.google.com/drive/folders/15LLFgV-S7tzmc48bvq9ZLJ8UtwEguKXT?usp=share_link`).

10.2 Avatar-Based Visual Feedback (Unity)

Visual feedback is provided through a virtual avatar developed in Unity, which reflects the classifier output in real time. During the feedback phase, the avatar executes the target movement only when the decoded motor intention matches the expected action, providing implicit and intuitive feedback.

Avatar personalization is supported to enhance user engagement and sense of ownership, while avoiding increased cognitive load during task execution. Different approaches for avatar creation were explored:

- Automatic avatar generation from a photograph using AI-based services such as AvatarSDK (`https://avatarsdk.com`).
- Manual avatar creation using Ready Player Me (`https://readyplayer.me`), providing Unity-ready avatars with customizable appearance.
- Automatic rigging and animation using Mixamo (`https://www.mixamo.com`), enabling rapid integration of humanoid animations within Unity.

A live demonstration of avatar integration and real-time feedback is available in the project repository: `https://drive.google.com/drive/folders/1uoKnXJvO2skppeW29h5gIjO2rU4gdMAN`

10.3 Monitoring Application Prototype (Figma)

The monitoring application prototype was developed to validate information architecture, accessibility strategies, and longitudinal data visualization for patients, caregivers, and clinicians.

The design process started with low-fidelity sketches to define core screens and navigation structure (see: `https://drive.google.com/drive/folders/1l_OxriVnufRWjdUBlpEazuMDjFcUKIb6`). These sketches were then translated into an interactive mid-fidelity prototype using Figma, allowing early evaluation of readability, interpretability of performance metrics, and role-based access (patient, caregiver, clinician).

The monitoring application is designed to:

- review session summaries,
- track longitudinal improvement,
- compare level progression across sessions,
- document clinical notes and recommendations,
- support personalization of the training experience outside the active training loop.

The interactive prototype is available at: `https://www.figma.com/design/4JW7qm4cgDYbretVs8oTp7/HMI-prototipo`

11 Evaluation

The evaluation of the proposed system is structured around three complementary evaluation dimensions:

- **System Performance**, assessing whether the system works as intended from a technical and functional perspective;
- **Usability and User Experience**, evaluating usability, cognitive workload, comfort, immersion, and overall interaction quality;
- **Stakeholder Perspective**, assessing the relevance and interpretability of the system for different user roles.

The evaluation focuses on two main evaluation targets:

- Training Game (VR interaction)
- Monitoring Application

and involves the following three user groups: Patients (primary users), Caregivers (support users),Clinicians / Therapists (professional users).
The following sections describe each evaluation dimension in detail.

11.1 System Performance Evaluation

Classifier-Related Metrics

System performance is first evaluated in terms of classifier reliability and stability during training sessions.

- Classification accuracy, computed over the 30 repetitions of each training level;
- Performance threshold: $\geq 85\%$ accuracy, used as a criterion for level progression; (Figure 1)
- Accuracy trends across levels and across sessions, to assess learning stability and consistency over time.

These metrics allow verification of whether the system provides reliable intention decoding before increasing task complexity.

An example of classifier performance for a representative subject is reported in Figure 1, which illustrates task-related cortical activation during motor imagery and high classification performance for both movement and no-movement classes.

Task Execution Metrics

To complement classifier performance, task execution metrics are used to assess interaction feasibility and engagement:

- Task completion rate, defined as completion of a full training level without interruption;
- Time-on-task, including:
  - setup time,
  - calibration time,
  - level execution time;
- Number of VR accesses, used as an indicator of engagement and adherence over repeated sessions.

11.2 Usability and User Experience Evaluation

Usability and user experience represent the core focus of the evaluation, given the cognitive demands of EEG-based interaction and the importance of long-term engagement in rehabilitation contexts.

Different evaluation methods are used for the training game and the monitoring application.

Training Game (VR Interaction)

The following standardized and custom tools are used:

- `System Usability Scale (SUS)`
  Used to assess overall perceived usability and ease of use of the training system.
- `NASA Task Load Index (NASA-TLX)`
  Used to evaluate perceived cognitive workload during motor imagery tasks, including mental demand, effort, and frustration.

- `Presence Questionnaire (PQ)`
  Used to assess the level of immersion and sense of presence within the virtual environment.
- `Simulator Sickness Questionnaire (SSQ)`
  Used to evaluate cybersickness symptoms potentially induced by VR exposure.
- `GUI Evaluation Questionnaire (Custom Items + User Experience Questionnaire)`
  A custom questionnaire combining ad-hoc items with the User Experience Questionnaire (UEQ) was developed to assess clarity of cues, feedback perception, motivation, and emotional response.

The latter one was implemented using Google Forms and administered to approximately 20 participants. Both the questionnaire and the collected responses are provided as supplementary material:

- Questionnaire link both Italian and English versions :
  - IT:
    `https://docs.google.com/forms/d/e/1FAIpQLSdILbjsUX4WOyE3PJKJ-FF5I-Kj4uhytZ56rRsIOgQFtGmxFw/viewform`
  - EN:
    `https://docs.google.com/forms/d/e/1FAIpQLSdzm4rahMVIVrDvUrT-FxIJdN7n06_3dbA3iNaDMk793EsKRw/viewform`
- Collected responses (Word document):
  `https://drive.google.com/drive/folders/1rR4_isbOcoDW-v6xgCvXWFtdYLoRCTV9?usp=share_link`

The insights obtained from these questionnaires were directly used to iteratively improve the training game interface, including visual clarity, feedback timing, and interaction flow.

For the Simulator Sickness Questionnaire, a dedicated interface was implemented to allow users to complete the SSQ immediately after the training session. Screenshots of the application used for SSQ administration are available at: `https://drive.google.com/drive/folders/1hfQzS8P6somix4JeQMoKDi3-xFSmcoIF?usp=share_link`

Monitoring Application

The monitoring application is evaluated using qualitative, interaction-centered methods, reflecting its exploratory and interpretative nature.

- Think-aloud protocol during app interaction, used to observe how users navigate summaries, trends, and clinician views while verbalizing their thoughts.
- Follow-up questions focusing on clarity, usefulness, and perceived value for long-term monitoring.

11.3 Stakeholder Perspective

To complement system performance and user experience evaluation, a stakeholder analysis was conducted to identify the actors involved in or affected by the proposed system, their interests, and their level of influence on design, adoption, and evaluation outcomes.

Primary Stakeholders

Primary stakeholders are directly involved in system use and evaluation.

- **End Users (Patients)**
  Profile: users with complete paralysis (EEG-only) and users with incomplete paralysis (EEG + EMG/IMU).
  Interests: regain autonomy, engage in meaningful training, reduce frustration, improve motor function.
  Influence: High — their needs directly guide interaction design, feedback strategies, and training structure.
- **Caregivers and Family Members**
  Role: support patients during training sessions, especially in home-based settings.
  Interests: ease of use, safety, supervision capabilities, reduction of caregiving burden.
  Influence: Medium — shape usability, accessibility, and monitoring requirements.
- **Clinicians (Physiatrists, Neurologists, Occupational Therapists)**
  Role: oversee therapy integration and clinical use.
  Interests: rehabilitation effectiveness, patient engagement, safety, measurable and interpretable progress.
  Influence: High — define clinical protocols, progression criteria, and integration feasibility.
- **Physiotherapists and Rehabilitation Specialists**
  Role: support daily training and progression.
  Interests: monitoring patient progress, adjusting training intensity, integration with conventional rehabilitation

exercises.
Influence: Medium — provide essential feedback on movement quality, usability, and task feasibility.

Secondary Stakeholders

Secondary stakeholders influence system development, deployment, and scalability.

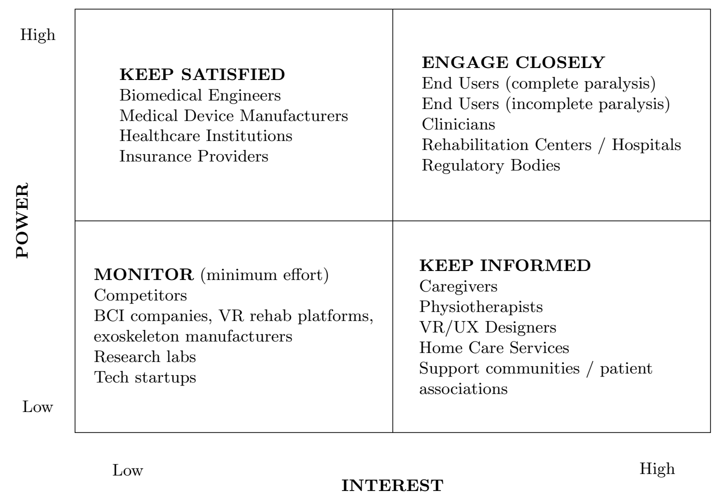
- **Biomedical Engineers and System Developers**
  Interests: system reliability, classifier accuracy, multimodal sensor integration, robust real-time performance.
  Influence: High — responsible for safe, stable, and reproducible implementation.
- **VR and UX Designers**
  Interests: intuitive, accessible, and motivating interaction design.
  Influence: Medium — impact cognitive load, engagement, and long-term adherence.
- **Medical Device and Sensor Manufacturers**
  Interests: hardware compatibility, regulatory compliance, integration with assistive devices.
  Influence: Medium–High — hardware constraints affect design and feasibility.
- **Hospitals, Rehabilitation Centers, and Home Care Services**
  Interests: cost-effectiveness, ease of integration, training efficiency, patient outcomes.
  Influence: High — determine real-world clinical adoption.
- **Healthcare Systems and Insurance Providers**
  Interests: reduction of long-term rehabilitation costs, improved outcomes.
  Influence: Medium — affect accessibility and large-scale deployment.
- **Regulatory and Ethical Bodies**
  Interests: patient safety, data protection, ethical use of neurotechnology.
  Influence: High — approval required before clinical deployment.

Tertiary Stakeholders (Competitors)

Competitors do not directly influence the project but shape market expectations, technological trends, and innovation pace.

- **BCI/Neurotechnology Companies (Neuralink, Emotiv, NextMind, OpenBCI):**
  Interests: Market expansion, innovation, defining EEG standards.
  Influence: Low-to-Medium — indirectly shape user expectations and benchmarks.
- **Rehabilitation Technology Companies (MindMaze, XRHealth, Neofect):**
  Interests: VR-based rehab platforms, sensor integration for movement training.
  Influence: Medium — impact clinical adoption trends and partnerships.
- **Exoskeleton & Prosthetic Manufacturers (Ekso Bionics, ReWalk Robotics, Ottobock):**
  Interests: Integrate intention-detection into devices, ensure compatibility with neuro-sensing technologies.
  Influence: Medium — affect long-term applicability to real exoskeletons.
- **Academic and Research Labs:** BCI labs, biomedical engineering departments, neurorehab research groups.
  Interests: Publish methods, test ML models, develop VR paradigms.
  Influence: Low-to-Medium — indirectly shape scientific expectations and validate approaches.

Stakeholder Map



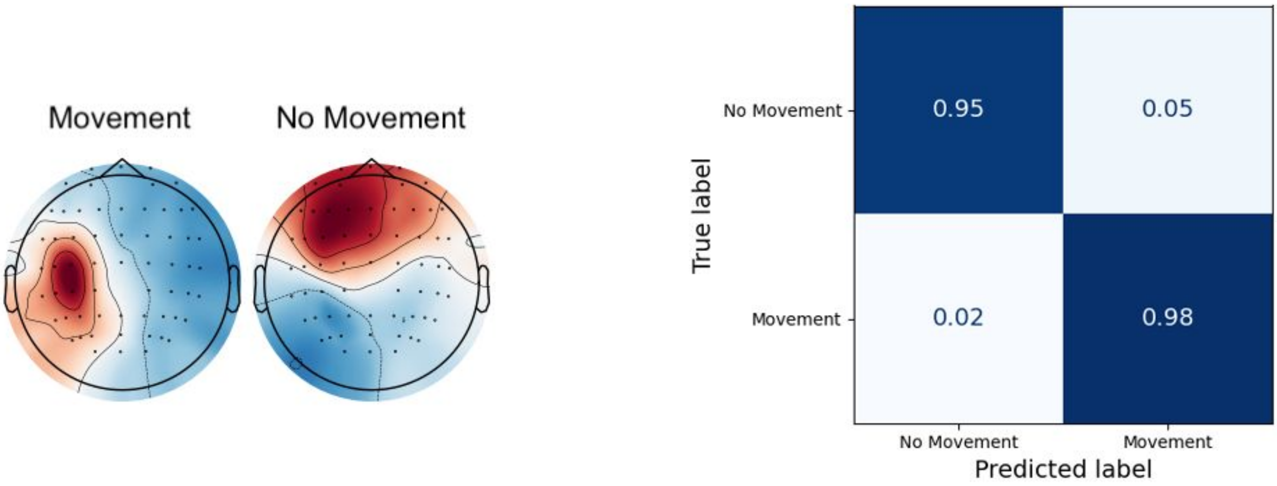


Figure 1: Results of the classifier training for a representative subject included in the study. The figure on the left shows that, during motor imagery, different cortical regions are activated. The figure on the right illustrates the classification performance, achieving an accuracy of 95% for the no-movement class and 98% for the movement class.

12 Ethical Considerations

Regarding ethical considerations, the protocol prioritizes participant well-being and data privacy through the following points:

- Participants will be provided informed consent
- The system avoids punitive feedback and uses supportive, non-judgmental wording
- EEG recordings are handled confidentially and anonymized
- Users may stop the session at any time for fatigue or discomfort
- The app avoids displaying clinically sensitive interpretations without professional context

Insights from both systems will inform the next design cycle and support future development of VR-based levels and multimodal BCI integration.

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