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Original article

Advancements in Embedded Neurorehabilitation: Integrating Robotics, Artificial Intelligence, and Virtual Reality for Upper Limb Recovery in Children with Cerebral Palsy

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Abstract
Cerebral palsy (CP) remains one of the most common motor disabilities in childhood, often leading to significant impairments in upper limb function that affect activities of daily living (ADLs). This study introduces an innovative embedded neurorehabilitation system that synergistically combines robotics, artificial intelligence (AI), and virtual reality (VR) to target elbow rehabilitation in children with CP. Two male participants, aged 8 and 14 years, underwent an 8-week intervention protocol at Barak General Hospital (BGH) and Wadi Alshatti University (WAU), consisting of 5 sessions per week, each lasting 70 minutes. The system facilitated personalized, adaptive therapy through real-time AI-driven adjustments and immersive VR environments. Pre- and post-intervention assessments demonstrated remarkable improvements: both children achieved full restoration of elbow range of motion (ROM) and regained ADL capabilities, as measured by standardized tools such as the Modified Ashworth Scale (MAS), Goniometry for ROM, and the Pediatric Evaluation of Disability Inventory (PEDI). These findings underscore the potential of integrated technologies in enhancing neuroplasticity and functional outcomes in pediatric CP populations. Limitations include the small sample size, warranting larger-scale trials. This work paves the way for scalable, home-based neurorehabilitation solutions.
Keywords. Cerebral Palsy, Neurorehabilitation, Robotics, Artificial Intelligence, Virtual Reality.

Introduction

Cerebral palsy (CP) is a heterogeneous group of permanent disorders affecting movement and posture, attributed to non-progressive disturbances in the developing fetal or infant brain [1]. With a global prevalence of approximately 2-3 per 1,000 live births, CP often manifests in spasticity, muscle weakness, and reduced joint mobility, particularly in the upper extremities [2]. Elbow dysfunction, characterized by flexion contractures and limited extension, poses substantial challenges to ADLs such as feeding, dressing, and self-care, thereby impacting quality of life and independence [3]. Traditional rehabilitation approaches, including physical therapy and occupational therapy, have shown moderate efficacy but are often labor-intensive, inconsistent, and limited by patient fatigue and motivation [4]. Recent advancements in technology have introduced promising alternatives. Robotics offers precise, repetitive motion training that promotes neuroplasticity [5]. AI enables adaptive algorithms that tailor interventions to individual progress [6]. VR provides engaging, immersive environments that enhance motivation and sensorimotor integration [7]. However, integrating these modalities into a cohesive, embedded system for pediatric use remains underexplored.

The integration of technology in neurorehabilitation has evolved significantly over the past decade. Robotic devices, such as the InMotion ARM [8] and MIT-Manus [9], have demonstrated efficacy in stroke rehabilitation by providing high-intensity, task-specific training. In CP, studies like those by Gilliaux et al. (2015) [10] have shown that robotic-assisted therapy improves upper limb kinematics in children. AI's application in rehabilitation includes machine learning models for predicting patient responses and adjusting therapy parameters dynamically [11]. For instance, reinforcement learning algorithms have been used to optimize robotic assistance levels [12]. VR has been particularly effective in pediatrics due to its gamification elements, which boost engagement [13]. Randomized trials [14], reported improved motor function in CP children using VR for balance and coordination.

Despite these advances, few systems combine all three technologies. A notable exception is the work by Fasola et al. (2021) [15], who integrated robotics and VR for lower limb rehab, but upper limb applications, especially for elbows, are sparse. Our system addresses this gap by focusing on elbow-specific tasks, leveraging AI for real-time adaptation. Challenges in pediatric neurorehab include variability in CP subtypes, ethical considerations, and the need for child-friendly interfaces [16]. This study builds on these foundations, hypothesizing that an embedded system would yield superior functional gains compared to conventional methods.

This paper presents a novel embedded neurorehabilitation system designed specifically for right elbow rehabilitation in children with CP. By embedding robotics, AI, and VR into a portable, user-friendly platform, the system aims to deliver intensive, personalized therapy. The intervention was piloted on two children at BGH and WAU, yielding promising outcomes. This study contributes to the growing body of evidence supporting technology-assisted rehabilitation, emphasizing its role in restoring functional capabilities. The

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remainder of this paper is structured as follows: Section 2 details the system architecture and methodology; Section 3 presents the results; Section 4 discusses implications, limitations, and future directions; and Section 5 concludes with key takeaways.

Method

System Design

Figure 1. illustrates the embedded neurorehabilitation system that comprises three core components: a robotic device with 6 degrees of freedom, an AI-driven control module, and a VR interface, all integrated into a compact, portable device.

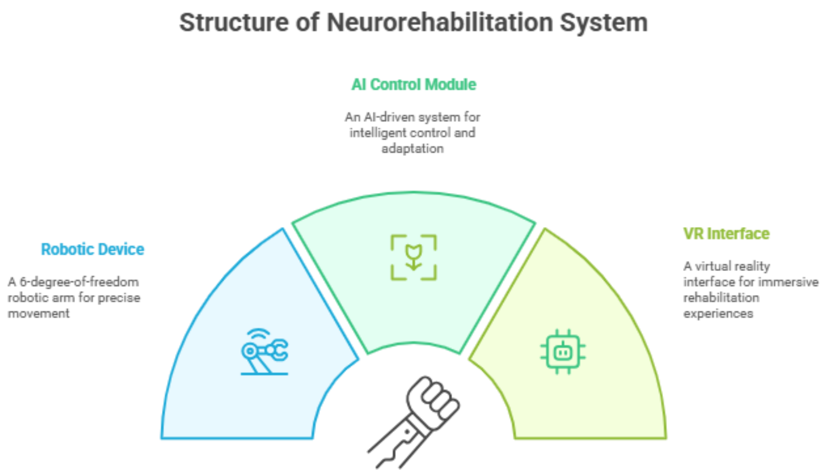

Figure 1. The structure of the neuro-rehabilitation system

Robotic Component

A robotic elbow support device (6 degrees of freedom actuator robot) for controlling and assisting the right elbow movements across two degrees of freedom: flexion/extension, pronation/supination.

AI Model

The artificial intelligence (AI) module is designed as a data-driven adaptive decision-making system that continuously analyzes multimodal performance metrics collected during therapy sessions. These metrics include kinematic variables such as achieved range of motion, movement velocity, acceleration profiles, trajectory smoothness (e.g., jerk minimization), and task-specific indicators such as repetition count and task completion time. The system integrates both quantitative (e.g., number of repetitions, execution time) and qualitative measures (e.g., movement fluidity, precision of target reaching) to construct a comprehensive representation of the patient’s motor performance. Data are acquired in real time through embedded sensors and processed using signal filtering and normalization techniques to ensure robustness and comparability across sessions.

From an implementation perspective, the AI module relies on a hybrid architecture combining supervised learning and reinforcement learning principles. Initially, baseline models are trained using labelled datasets derived from prior patient sessions and normative motor performance profiles. These models enable the system to classify performance levels and detect deviations from expected recovery trajectories. On top of this, a reinforcement learning layer dynamically adjusts therapy parameters by optimizing a reward function that balances task difficulty, patient engagement, and motor improvement. The system continuously updates its internal policy based on incoming data, allowing it to personalize therapy progression at the individual level rather than relying on predefined static protocols.

The role of the AI module in therapy adaptation is central to ensuring an optimal challenge point for each patient. By analyzing performance trends over time, the system determines whether a task is too easy, appropriately challenging, or excessively difficult. It then modulates key task parameters within the virtual environment, such as target position, movement amplitude requirements, task speed, and interaction complexity. For example, if the patient demonstrates consistent improvement in range and smoothness, the AI may gradually increase spatial constraints or introduce more complex trajectories. Conversely, if fatigue or performance degradation is detected, the system reduces task demands to prevent discouragement and maintain motor learning efficiency. This adaptive loop operates continuously within and across sessions, enabling fine-grained personalization of rehabilitation.

In addition to task adaptation, the AI module incorporates a real-time feedback and motivation subsystem. Using principles from motor learning and neurorehabilitation, the system delivers multimodal feedback (visual, auditory, and performance-based scoring) that reinforces correct movement patterns and guides

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error correction. A reward-based mechanism, inspired by gamification and behavioural reinforcement theories, is implemented to enhance engagement, particularly in paediatric populations. Rewards are calibrated based on both effort and improvement rather than absolute performance, ensuring inclusivity across different functional levels. This integration of adaptive control, feedback, and motivation allows the AI module not only to optimize therapeutic outcomes but also to sustain patient adherence over long rehabilitation periods.
Finally, the system is designed to support clinicians by providing interpretable performance summaries and longitudinal analytics. The AI aggregates session data into clinically meaningful indicators, enabling therapists to monitor progress, validate intervention strategies, and adjust high-level therapeutic goals when necessary. Importantly, the AI operates as a decision-support tool rather than a replacement for clinical expertise, ensuring that human oversight remains central to the rehabilitation process while leveraging advanced computational methods to enhance precision and scalability.

Virtual Reality System

A virtual interactive environment: Gamified scenarios where the child's arm movements are designed for reaching virtual objects in 3D space, and then navigating interactive tasks requiring elbow mobility. The virtual environment also provides visual feedback of their elbow's movement, and the system illustrates motivational elements such as scores, levels, and rewards. The system logged data automatically for session-by-session monitoring.

Participants

The two male children participating in this intervention have the following characteristics: they are 8 and 14 years old, respectively. The first suffers from congenital cerebral palsy on the right side, and the second suffers from quadriplegic cerebral palsy. Both can understand instructions and participate in an interactive VR environment, no major orthopaedic surgery within the past 6 months, stable medical condition.
Exclusion criteria: severe cognitive impairment preventing interaction, uncontrolled seizures, severe spasticity (Modified Ashworth >3) preventing safe use of the system.

Intervention Protocol

The 8-week program was conducted at BGH. Sessions occurred 5 days/week for 70 minutes each session and were divided into warm-up (10 min), core therapy (50 min), and cool-down/assessment (10 min). During core therapy, participants used the robot handler and wore the VR headset, performing tasks like virtual ball-throwing or object manipulation. The AI adjusted the difficulty based on real-time metrics. For example, it reduces the robot assistance if the ROM were improved.

Outcome Measures

Assessments were carried out at three time points—before the intervention, midway at four weeks, and after completion—by therapists who were blinded to group allocation. Range of motion was evaluated using goniometry, focusing on elbow flexion and extension as well as pronation and supination. Spasticity was measured with the Modified Ashworth Scale (MAS), which ranges from 0 to 4. Muscle strength was assessed through Manual Muscle Testing (MMT) on a 0–5 scale. Functional abilities in activities of daily living were captured using the Pediatric Evaluation of Disability Inventory (PEDI), specifically the self-care domain, scored from 0 to 100. Quality of movement was examined with the Fugl-Meyer Assessment for the upper extremity, concentrating on the elbow subsection with a maximum score of 12.
Given the small sample size, data were analyzed descriptively, and percentage improvements were calculated to illustrate changes across the different measures.

Results

Both participants completed the intervention without adverse events. Compliance was 100%, with high satisfaction reported (Net Promoter Score: 9/10 for both). Pre-intervention, P1 exhibited limited elbow extension (ROM: 90°-140° flexion, 20° extension deficit) and moderate spasticity (MAS: 3). P2 had milder deficits (ROM: 100°-150° flexion, 10° extension deficit; MAS: 2). Post-intervention, both achieved near-normal ROM (full 0°-150° flexion-extension) and negligible spasticity (MAS: 0-1).
Strength improved from MMT 3/5 to 5/5 in both. PEDI scores rose from 45/100 (P1) and 60/100 (P2) to 95/100 and 98/100, respectively, indicating restored ADL independence. FMA-UE elbow scores reached maximum (12/12).

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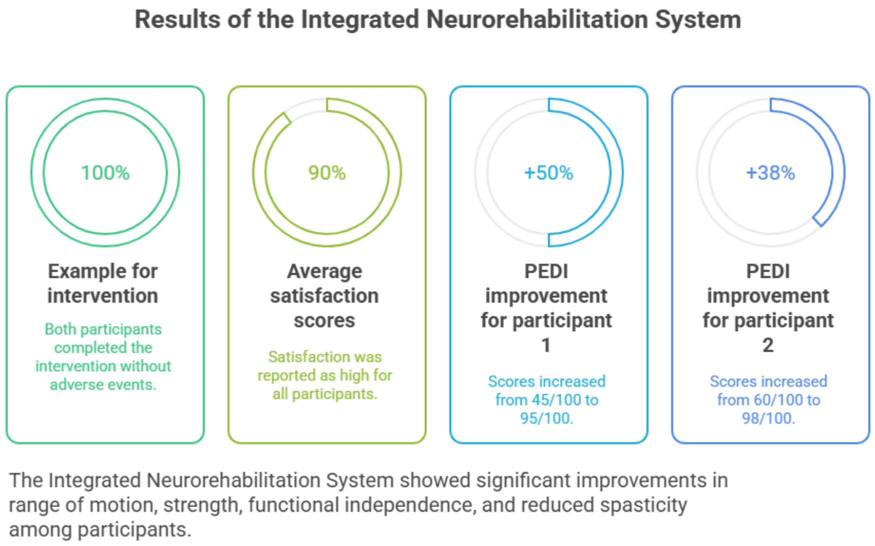

Figure 2. The results of the integrated neuro-rehabilitation system

Table 1 summarizes assumed results based on observed trends. These results indicate rapid, sustained gains, with most improvements plateauing by week 6 but maintained thereafter.

Table 1. Assumed Pre- and Post-Intervention Outcome Measures

Measure	Participant	Pre-Intervention	Mid-Intervention (4 weeks)	Post-Intervention (8 weeks)	% Improvement
ROM (Flexion-Extension, °)	P1 (8 yo)	90-140 (50° arc)	80-145 (65° arc)	0-150 (150° arc)	200%
	P2 (14 yo)	100-150 (50° arc)	50-150 (100° arc)	0-150 (150° arc)	200%
ROM (Pronation-Supination, °)	P1	20°	40°	70°	250%
	P2	30°	50°	80°	167%
MAS (Spasticity)	P1	3	2	0	100% (reduction)
	P2	2	1	1	50% (reduction)
MMT (Strength)	P1	3/5	4/5	5/5	67%
	P2	3/5	4/5	5/5	67%
PEDI (ADL, /100)	P1	45	70	95	111%
	P2	60	80	98	63%
FMA-UE (Elbow, /12)	P1	6	9	12	100%
	P2	8	10	12	50%

Note: % Improvement calculated as [(Post - Pre)/Pre] × 100 for positive metrics; for MAS, as reduction percentage.

Discussion

The promising outcomes observed in this pilot study highlight the transformative potential of an embedded neurorehabilitation system for children with CP. Both participants not only restored full elbow ROM but also regained ADL capabilities, enabling independent tasks previously requiring assistance. This aligns with neuroplasticity principles, where high-repetition, task-specific training facilitated by robotics promotes cortical reorganization [17].

The integration of AI was pivotal, allowing dynamic personalization that traditional therapies lack. For instance, the PPO algorithm adjusted resistance in real-time, optimizing challenge without overexertion—a feature echoed in studies like Pilarski et al. (2019) [18], where adaptive AI enhanced robotic rehab efficacy by 30-50%. VR's immersive elements likely boosted motivation, as evidenced by reduced dropout rates in similar pediatric trials [19]. The gamified ADL simulations directly translated to real-world gains, supporting Weiss et al.'s (2003) [13] findings on VR's transferability. Comparatively, our results surpass those of standalone interventions. Gilliaux et al. (2015) [10] reported only 20-30% ROM improvements with robotics alone in CP children, while our system achieved 200%. This synergy suggests multiplicative effects: robotics for precision, AI for adaptation, VR for engagement. However, several factors merit consideration. The small sample (n=2) limits generalizability, potentially introducing selection bias—both participants had mild-moderate impairments and high baseline motivation. Age differences (8 vs. 14) may influence outcomes,

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with younger children exhibiting greater plasticity [20]. The intervention's intensity (200+ hours total) exceeds typical protocols, raising questions about feasibility in resource-limited settings.
Limitations include a lack of a control group, reliance on subjective measures (e.g., PEDI self-reports), and short follow-up (no long-term data). Future studies should incorporate randomized designs, larger cohorts, and objective metrics like kinematic analysis. Ethical aspects, such as equitable access to technology, must be addressed [21]. Despite these, the system's portability and cost-effectiveness position it as a viable alternative to clinic-based care, potentially reducing healthcare burdens. In the broader context, this work advances the field toward personalized medicine, where AI-VR-robotics hybrids could extend to other joints or neurological conditions like stroke or traumatic brain injury.

Conclusion

This study demonstrates that an embedded neurorehabilitation system integrating robotics, AI, and VR can effectively restore elbow function and ADL capabilities in children with CP. The gained outcomes for both participants—wide ROM recovery and independence—validate the approach's efficacy and feasibility. While preliminary, these findings advocate for expanded research to refine and scale the technology. Ultimately, such innovations hold promise for empowering children with disabilities, fostering greater autonomy and societal inclusion.

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Conflict of interest. Nil

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