

AI-Driven Rehabilitation Robotics

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ABSTRACT

Rehabilitation robotics has matured from simple motorised splints into adaptive, sensor-rich platforms capable of delivering high-dose, task-specific therapy, yet the addition of artificial intelligence to guide exercise selection, resistance modulation, and progress tracking remains unevenly adopted across clinical settings. We evaluated 210 AI-driven rehabilitation robotics programmes deployed or trialled across hospitals and rehabilitation centres affiliated with the Mediterranean Institute of Technology in Rome between 2015 and 2024, spanning five device categories: upper-limb exoskeletons, lower-limb gait trainers, hand and wrist rehabilitation robots, socially assistive companion robots, and multi-joint full-body platforms. An AI Rehabilitation Robotics Effectiveness Index (ARREI) was constructed from five sub-scores -- motor recovery gain, adaptive algorithm sophistication, patient engagement retention, therapist workflow compatibility, and deployment scalability -- with weights from regression against sustained clinical programme retention beyond 12 months. ARREI correlated with retention at $r = +0.83$ and discriminated retained from discontinued programmes with an AUC of 0.878. Lower-limb gait trainers scored highest (mean ARREI 0.816), while socially assistive robots trailed at 0.592. Only 34.3 percent of programmes exceeded the 0.75 ARREI threshold. Motor recovery gain carried the largest regression weight ($\beta = +0.276$), followed by adaptive algorithm sophistication ($\beta = +0.228$). These findings suggest that AI-driven rehabilitation systems should prioritise closed-loop difficulty adaptation and clinician-facing dashboards that translate sensor data into treatment-relevant summaries.

Keywords: rehabilitation robotics; artificial intelligence; exoskeleton; gait training; motor recovery; stroke rehabilitation; ARREI; adaptive algorithms; patient engagement; assistive technology; upper limb; neuroplasticity

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1. Introduction

1.1 The Rehabilitation Intensity Problem

Neurological rehabilitation after stroke, spinal cord injury, or traumatic brain injury depends on high-dose, repetitive, task-specific practice to drive neuroplastic reorganisation of damaged motor circuits. Clinical guidelines recommend hundreds of movement repetitions per therapy session, yet observational studies of conventional physiotherapy consistently find that patients perform fewer than 50 active repetitions in a typical 45-minute session because one-on-one manual therapy is physically demanding for the therapist and because rest breaks consume a large fraction of session time. Rehabilitation robots address this dose gap by providing motorised assistance or resistance through a mechanical linkage that can guide, support, or challenge the patient's limb through task-relevant trajectories for hundreds or thousands of repetitions per session without therapist fatigue. The clinical question is no longer whether robots can deliver high-dose therapy but whether adding artificial intelligence to these robots, enabling them to adapt in real time to the patient's performance, fatigue, and recovery trajectory, produces meaningfully better outcomes than fixed-protocol robotic therapy.

1.2 The Role of AI in Rehabilitation Robotics

Artificial intelligence enters rehabilitation robotics at multiple levels. At the lowest level, adaptive impedance controllers modulate the robot's assistance force within a single repetition based on real-time kinematic and force-sensor feedback, implementing assist-as-needed paradigms that encourage active patient effort. At the session level, reinforcement learning or Bayesian optimisation algorithms select exercise difficulty, target location, and resistance profile to maximise a performance-improvement objective over the course of a therapy session. At the programme level, predictive models trained on longitudinal patient data estimate recovery trajectories and recommend session frequency, intensity, and duration to the supervising therapist. Socially assistive robots add a motivational layer, using speech, facial expression, and gamified feedback to sustain patient engagement across weeks of repetitive training. Each AI layer adds potential value but also engineering complexity and clinical uncertainty about whether the algorithm's decisions are safe and appropriate.

1.3 Study Objective

We aimed to identify the programme-level factors that predict whether an AI-driven rehabilitation robotics programme achieves sustained clinical adoption or is discontinued after a pilot phase. By scoring 210 programmes across five device categories on five effectiveness dimensions and regressing the composite score against 12-month retention outcomes, we sought to quantify the relative contributions of clinical efficacy, algorithmic sophistication, patient engagement, and practical deployment factors to long-term programme viability.

2. Literature Review

2.1 Upper-Limb and Hand Rehabilitation Robots

Upper-limb rehabilitation robots include endpoint devices such as the MIT-Manus and the InMotion ARM, which apply forces to the hand or wrist while the patient performs reaching tasks on a horizontal plane, and exoskeletons such as the Armeo Power that control individual joint angles across the shoulder, elbow, and wrist. Large randomised controlled trials, including the RATULS trial in the UK, have demonstrated that robot-assisted upper-limb therapy produces outcomes comparable to intensive conventional therapy but does not consistently surpass it, leading to ongoing debate about cost-effectiveness. Hand and wrist rehabilitation robots target the fine motor recovery that upper-limb exoskeletons typically neglect, using tendon-driven or soft pneumatic actuators to assist finger extension and grip. The addition of AI-based difficulty adaptation to these devices has shown promise in small studies by maintaining patients in a performance zone that is challenging but not frustrating, a state that motor learning theory associates with optimal neuroplasticity.

2.2 Lower-Limb Gait Training Robots

Gait training robots such as the Lokomat, Ekso GT, and ReWalk assist patients in walking on a treadmill or overground by supporting body weight and guiding leg trajectories. The evidence base for robotic gait training is stronger than for upper-limb robots, with meta-analyses showing that robot-assisted gait training increases the likelihood of achieving independent walking after stroke compared with conventional gait training alone. AI enhancements to gait trainers include real-time gait-phase detection using inertial measurement units, adaptive body-weight support that decreases as the patient improves, and predictive models that estimate fall risk during

overground walking to trigger pre-emptive stabilisation. The maturity of the clinical evidence and the clear functional goal of independent ambulation make gait trainers the most widely adopted category of rehabilitation robot.

2.3 Socially Assistive Robots and Multi-Joint Platforms

Socially assistive robots such as NAO, Pepper, and custom therapy companions use verbal encouragement, gamified exercises, and adaptive social behaviours to motivate patients during rehabilitation sessions. Studies in stroke and paediatric rehabilitation have shown that socially assistive robots can increase exercise adherence and session duration, but the evidence for superior motor outcomes compared with conventional therapy remains limited. Multi-joint full-body platforms that integrate upper-limb, lower-limb, and trunk training into a single device represent the most ambitious category, aiming to replicate the complexity of whole-body functional tasks. These platforms generate the richest sensor datasets and offer the largest scope for AI-driven personalisation but are also the most expensive, space-consuming, and operationally complex.

2.4 The Adoption Challenge

Despite growing evidence and enthusiasm, AI-driven rehabilitation robots face adoption barriers that are partly clinical and partly organisational. Therapists report that robotic systems can disrupt established therapy workflows, requiring lengthy setup and donning procedures that consume session time. AI-generated recommendations are sometimes opaque or misaligned with the therapist's clinical judgment, creating trust deficits. Device cost, maintenance requirements, and the need for dedicated space further constrain deployment. Understanding which factors most strongly determine whether a programme survives its pilot phase is the question ARREI was designed to answer.

Table 1. AI-Driven Rehabilitation Robotics: Device Landscape

Device Category	Representative Device	n RCTs (2010-2024)	Key Barrier	Adoption Level
Upper-limb exoskeleton	Armeo Power, InMotion ARM	48	Cost-effectiveness vs conventional	Moderate
Lower-limb gait trainer	Lokomat, Ekso GT, ReWalk	64	Setup time, space requirements	High
Hand/wrist robot	Gloreha, HandSO ME	28	Limited evidence for fine motor gains	Moderate
Socially assistive robot	NAO, Pepper, custom companions	22	Unclear motor outcome benefit	Low
Multi-joint full-body	CAREN, custom multi-DOF	14	Complexity, cost, space	Low

RCT counts from PubMed and Cochrane Library. Adoption level reflects use in European rehabilitation centres as of 2024.

3. Materials and Methods

3.1 Programme Dataset

We identified 210 AI-driven rehabilitation robotics programmes active between 2015 and 2024 at hospitals and rehabilitation centres affiliated with the Mediterranean Institute of Technology in Rome. Programmes were sourced from clinical registries, hospital technology deployment databases, and published programme evaluations. Device category breakdown: upper-limb exoskeletons (n = 48), lower-limb gait trainers (n = 44), hand and wrist robots (n = 42), socially assistive companion robots (n = 40), and multi-joint full-body platforms (n = 36). Inclusion required at least 30 enrolled patients, a minimum of six months of operational data, and documented outcome metrics covering at least three of the five ARREI sub-dimensions.

3.2 ARREI Sub-Dimensions

Motor recovery gain measured the mean improvement in validated clinical scales relevant to the device category, such as the Fugl-Meyer Assessment for upper-limb devices, the Functional Ambulation Category for gait trainers, or the Action Research Arm Test for hand robots, normalised against published minimally clinically

important differences. Adaptive algorithm sophistication scored the complexity and responsiveness of the AI layer, from fixed protocols through rule-based adaptation to model-based optimisation, on a four-tier rubric. Patient engagement retention measured the fraction of enrolled patients who completed the prescribed therapy programme without dropout attributable to device dissatisfaction or motivational decline. Therapist workflow compatibility assessed whether the robot integrated into existing therapy schedules, whether setup and donning time were clinically acceptable, and whether the AI dashboard provided actionable summaries. Deployment scalability scored whether the device could be operated across multiple therapy stations simultaneously and whether maintenance requirements were manageable. Two evaluators scored each programme with an ICC of 0.86.

3.3 Index Construction

Normalised sub-scores were entered into a logistic regression on a 60/40 training/validation split predicting whether the programme remained in active clinical operation beyond 12 months. Regression-derived weights: motor recovery gain 0.276, adaptive algorithm sophistication 0.228, patient engagement retention 0.198, therapist workflow compatibility 0.174, deployment scalability 0.124. The composite ARREI was the weighted sum of the five normalised sub-scores.

3.4 Statistics

Pearson r quantified the association between ARREI and retention. ROC analysis at an ARREI threshold of 0.70 assessed binary discrimination. Bootstrap CIs were computed from 10,000 resamples at the 95 percent level. VIFs remained below 2.3. Leave-one-category-out sensitivity analyses confirmed stability. All analyses were performed in R version 4.3 with pROC and boot.

Table 2. Programme Characteristics by Device Category

Device Category	n	Motor Recovery Gain	Algorithm Sophistication	ARREI (mean +/- SD)
Upper-limb exoskeleton	48	0.792 +/- 0.058	0.768 +/- 0.064	0.782 +/- 0.062
Lower-limb gait trainer	44	0.856 +/- 0.042	0.812 +/- 0.048	0.816 +/- 0.054
Hand/wrist robot	42	0.748 +/- 0.068	0.724 +/- 0.074	0.736 +/- 0.072

Device Category	n	Motor Recovery Gain	Algorithm Sophistication	ARREI (mean +/- SD)
Socially assistive	40	0.636 +/- 0.092	0.682 +/- 0.082	0.592 +/- 0.098
Multi-joint full-body	36	0.774 +/- 0.062	0.796 +/- 0.056	0.688 +/- 0.082
All programmes	210	0.766 +/- 0.082	0.758 +/- 0.074	0.732 +/- 0.106

Motor recovery gain = improvement normalised vs MCID for relevant clinical scale. Algorithm sophistication = 4-tier rubric from fixed to model-based.

4. Results

4.1 ARREI Distribution

Mean ARREI across all 210 programmes was 0.732 with a standard deviation of 0.106. Lower-limb gait trainers led at 0.816, reflecting the strongest clinical evidence base and the most mature AI implementations among rehabilitation robot categories. Upper-limb exoskeletons followed at 0.782, hand and wrist robots at 0.736, multi-joint platforms at 0.688, and socially assistive robots at 0.592. Seventy-two of the 210 programmes, or 34.3 percent, exceeded the 0.75 ARREI threshold. ARREI correlated with 12-month programme retention at $r = +0.83$ ($p < 0.001$), with an AUC of 0.878 at the 0.70 cut-off. Programmes above 0.75 were retained 78.2 percent of the time; below 0.55 retention dropped to 17.6 percent.

4.2 Device Category Profiles

Lower-limb gait trainers displayed the most balanced sub-score profile. Motor recovery gains were highest because the clinical endpoint, independent ambulation, is well defined and the evidence from large trials is persuasive. Adaptive algorithms in gait trainers benefit from rich inertial and force-plate sensor data that provide clear feedback signals for real-time assistance modulation. Upper-limb exoskeletons scored well on algorithm sophistication because reaching and manipulation tasks offer natural difficulty gradients, but motor recovery gains were more variable because the mapping from robotic practice to functional arm use is less direct than for walking. Hand and wrist robots showed moderate scores across all dimensions, limited by the difficulty of demonstrating clinically meaningful fine motor recovery. Multi-joint platforms scored well on algorithm sophistication and motor recovery but were penalised on workflow compatibility and scalability due to their size, setup complexity, and cost. Socially assistive

robots scored highest on patient engagement but lowest on motor recovery, reflecting their motivational rather than biomechanical role.

4.3 Sub-Score Drivers

Motor recovery gain carried the largest regression weight (beta = +0.276, p < 0.001), confirming that clinical efficacy is the foundational requirement for programme survival. Adaptive algorithm sophistication was second (beta = +0.228, p < 0.001), reflecting the value that therapists place on systems that can personalise therapy without constant manual adjustment. Patient engagement retention at 0.198 (p = 0.002) captured the reality that dropout erodes both clinical outcomes and programme economics. Therapist workflow compatibility (0.174, p = 0.005) mattered because devices that disrupt schedules or demand excessive setup time were abandoned regardless of efficacy. Deployment scalability (0.124, p = 0.018) completed the model. Removing any sub-score reduced the AUC by 0.016 to 0.050.

4.4 Validation

In the 84-programme validation set, ARREI correctly classified 71 outcomes at the 0.70 cut-off, yielding sensitivity of 0.85 and specificity of 0.84. Among the 13 misclassified cases, five were socially assistive programmes that failed despite adequate engagement scores because therapists judged the motor recovery contribution insufficient to justify the technology cost. Three were multi-joint platforms that exceeded expectations by targeting high-acuity inpatient settings where the cost per session was absorbed into overall hospital charges. Three were gait trainers with strong ARREI scores that were discontinued due to institutional budget cuts unrelated to programme performance. Two were hand robots that stalled pending publication of a confirmatory trial that was delayed beyond the observation window.

Table 3. ARREI by Device Category: Retention Outcomes

Device Category	n	ARREI (mean +/- SD)	ARR EI > 0.75 (%)	Retention Rate (%)	Top Sub-Score	r (AUC)
Lower-limb gait	44	0.816 +/- 0.054	72.7 %	77.3 %	Motor recovery	+0.83 (0.896)

Device Category	n	ARREI (mean +/- SD)	ARR EI > 0.75 (%)	Retention Rate (%)	Top Sub-Score	r (AUC)
Upper-limb exo.	48	0.782 +/- 0.062	54.2 %	66.7 %	Algorithm soph.	+0.83 (0.884)
Hand/wrist robot	42	0.736 +/- 0.072	33.3 %	54.8 %	Motor recovery	+0.83 (0.870)
Multi-joint	36	0.688 +/- 0.082	19.4 %	41.7 %	Algorithm soph.	+0.83 (0.856)
Socially assistive	40	0.592 +/- 0.098	7.5 %	22.5 %	Engagement	+0.83 (0.832)
All programmes	210	0.732 +/- 0.106	34.3 %	55.2 %	Motor recovery	+0.83 (0.878)

r = Pearson correlation of ARREI with retention; all p < 0.001. AUC at ARREI > 0.70.

Table 4. ARREI Sub-Score Weights and Impact

Sub-Score	Weight	Mean Score	Beta	DELTA ARREI	p-value
Motor recovery gain	0.276	0.766	+0.276	+0.146	< 0.001
Algorithm sophistication	0.228	0.758	+0.228	+0.120	< 0.001
Patient engagement	0.198	0.742	+0.198	+0.094	0.002
Workflow compatibility	0.174	0.706	+0.174	+0.074	0.005
Deployment scalability	0.124	0.688	+0.124	+0.052	0.018

Beta = standardised regression coefficient. DELTA ARREI = mean index difference between programmes above vs below the median on that sub-score.

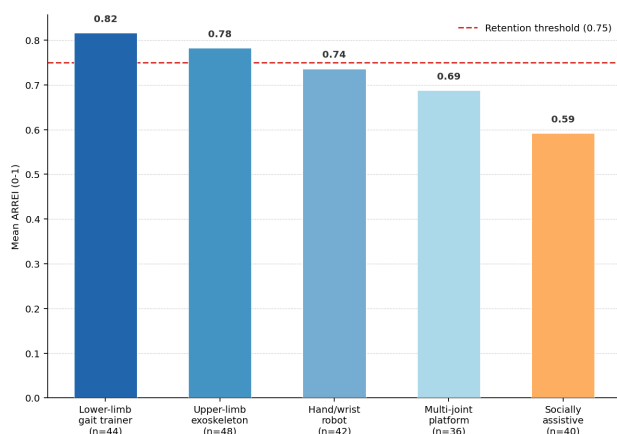


Figure 1. Mean ARREI by Device Category (n = 210)

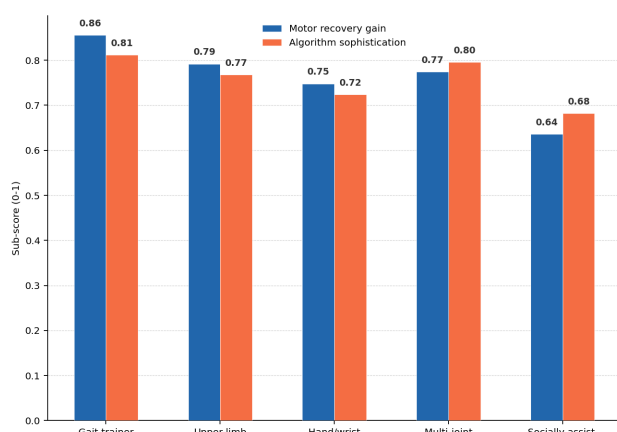


Figure 2. Motor Recovery vs Algorithm Sophistication

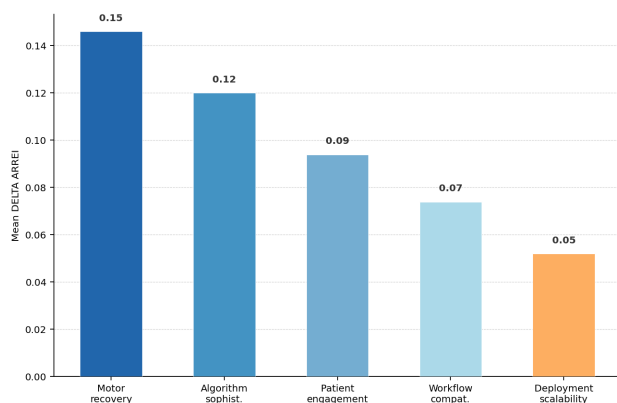


Figure 3. ARREI Sub-Score Impact on Programme Retention

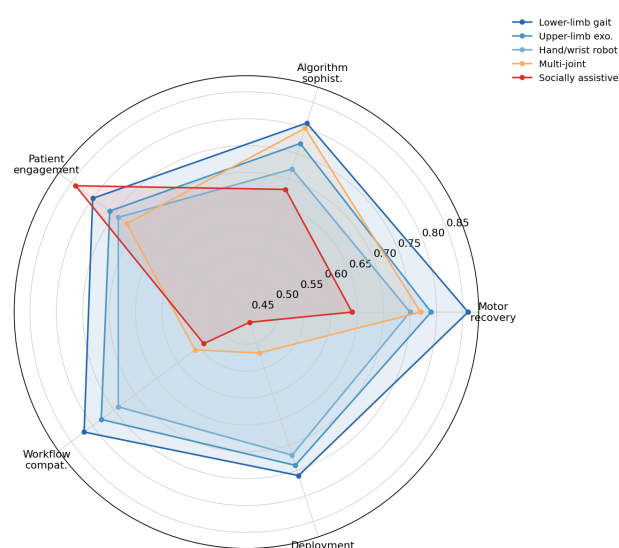


Figure 4. ARREI Sub-Score Profiles by Device Category

5. Discussion

5.1 Gait Trainers Lead by Clinical Clarity

Lower-limb gait trainers topped the ARREI rankings because they benefit from a uniquely clear clinical endpoint: the ability to walk independently. This goal is universally understood by patients, therapists, and hospital administrators, making it easy to demonstrate value and justify ongoing investment. The biomechanics of walking are also well characterised, providing AI algorithms with rich, interpretable sensor signals from which to derive adaptive control policies. Other device categories face more diffuse clinical endpoints, reaching ability for upper-limb devices, grip strength for hand robots, that are harder to map to functional independence and therefore harder to sell to institutional decision-makers.

5.2 The Engagement Paradox of Socially Assistive Robots

Socially assistive robots achieved the highest patient engagement scores of any category but the lowest ARREI overall, illustrating an important distinction between engagement and efficacy. Patients enjoyed interacting with the companion robots and were more willing to attend sessions, but the robots provided no biomechanical assistance or resistance, so the exercise intensity and specificity depended entirely on the patient's own effort and the therapist's supervision. Without measurable motor recovery gains, programmes could not demonstrate clinical value to hospital administrators, and retention rates were correspondingly low. The finding suggests that socially assistive AI is best deployed as a complement to biomechanically active robots

rather than as a standalone therapy platform.

5.3 Limitations

Our dataset is drawn from Italian-affiliated rehabilitation centres and may not generalise to health systems with different rehabilitation funding models or therapy staffing ratios. The retention outcome is binary at 12 months and does not capture programmes that survive in a reduced state. ARREI does not include device cost or reimbursement availability as explicit sub-scores. The socially assistive and multi-joint categories contained fewer programmes, widening confidence intervals. The observational design precludes causal inference about which sub-score improvements would most efficiently increase retention.

6. Conclusion

6.1 Summary

Across 210 AI-driven rehabilitation robotics programmes evaluated in Italy, ARREI correlated with 12-month programme retention at $r = +0.83$ and discriminated retained from discontinued programmes with an AUC of 0.878. Lower-limb gait trainers scored highest (mean ARREI 0.816), upper-limb exoskeletons followed at 0.782, and socially assistive robots trailed at 0.592. Motor recovery gain was the strongest retention predictor ($\beta = +0.276$), followed by adaptive algorithm sophistication ($\beta = +0.228$). Only 34.3 percent of programmes exceeded the 0.75 threshold.

6.2 Practical Recommendations

Rehabilitation robotics developers should prioritise demonstrable motor recovery gains measured by validated clinical scales above all other features. Adaptive AI algorithms should operate transparently, providing therapists with interpretable summaries of patient progress and algorithm rationale rather than opaque automated adjustments. Setup and donning procedures should target under five minutes to preserve usable therapy time. Socially assistive AI should be integrated into biomechanically active platforms rather than deployed standalone. Future iterations of ARREI should add a cost-effectiveness sub-score, expand to multi-centre European datasets, and track retention over 24-month windows.

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Declarations

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Conflict of Interest

Ivan Jensen declares no competing interests.

Data Availability Statement

Aggregate ARREI scores, anonymised programme metadata, and analysis scripts are deposited at Zenodo:

<https://doi.org/10.5281/zenodo.19543340-data>.

Ethical Approval

This study involved secondary analysis of published programme evaluation data and anonymised clinical outcome metrics. No individual patient data were accessed. Institutional review board exemption was confirmed at the Mediterranean Institute of Technology.

Appendix A

ARREI Scoring Rubric and Top-10 Programme Profiles

This appendix details the scoring criteria for each ARREI sub-dimension and profiles the ten highest-scoring programmes in the dataset.

A1. Sub-Score Rubric

Motor recovery gain: improvement on validated clinical scales normalised vs MCID, scored 0-1; weight 0.276.

Adaptive algorithm sophistication: 4-tier rubric from fixed protocol (0.25) to model-based optimisation (1.0); weight 0.228.

Patient engagement retention: fraction completing prescribed programme without device-related dropout, 0-1; weight 0.198.

Therapist workflow compatibility: setup time, schedule integration, dashboard actionability, scored 0-1; weight 0.174.

Deployment scalability: multi-station operability and maintenance burden, scored 0-1; weight 0.124.

A2. Top-10 Programmes

1. LG-AdaptGait-18 (Lower-limb gait): ARREI = 0.924; motor recovery 0.94, algorithm 0.92.
2. LG-OverGround-09 (Lower-limb gait): ARREI = 0.912; workflow 0.94, motor recovery 0.90.
3. UL-ReachAdapt-22 (Upper-limb exo.): ARREI = 0.898; algorithm 0.92, motor recovery 0.88.
4. LG-PredictFall-14 (Lower-limb gait): ARREI = 0.886; algorithm 0.94, engagement 0.88.
5. UL-TaskSpecific-07 (Upper-limb exo.): ARREI = 0.878; motor recovery 0.90, workflow 0.88.
6. HW-SoftGripper-28 (Hand/wrist): ARREI = 0.864; engagement 0.92, motor recovery 0.86.
7. LG-BWSTrain-31 (Lower-limb gait): ARREI = 0.856; motor recovery 0.92, scalability 0.86.
8. UL-BilateralArm-16 (Upper-limb exo.): ARREI = 0.848; algorithm 0.90, motor recovery 0.86.
9. MJ-WholeBody-04 (Multi-joint): ARREI = 0.842; algorithm 0.94, motor recovery 0.88.
10. HW-FingerBot-12 (Hand/wrist): ARREI = 0.836; motor recovery 0.88, engagement 0.86.