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Artificial Intelligence and Robotic Technologies for Post-Stroke Fine Motor Neurorehabilitation: A Scoping Review

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ABSTRACT

Objective

To explore the use of artificial intelligence (AI) and robotic technologies in fine motor rehabilitation of the upper limb after stroke and their implications for occupational therapy.

Methods

A scoping review was conducted following the PRISMA-ScR guidelines. A scoping review was conducted following the PRISMA-ScR guidelines. The first author conducted database searches in PubMed/MEDLINE, CINAHL, IEEE Xplore, and the Cochrane Library in [Month Year], using the strategy detailed in Appendix A. The search covered studies published from January 2010 to December 2025. Reference lists of included studies and relevant reviews were hand-searched. All search results were exported, deduplicated, and screened by [Author initials]. The final evidence map was verified against accessible full-text records on June 26, 2026.The studies included adults post-stroke and focused on AI-enabled, brain-computer interface, robotic, sensor-based, or digitally adaptive interventions aimed at improving hand, finger, grasp, release, pinch, or dexterity. Data were collected on population, technology type, AI or digital function, intervention context, outcome measures and main clinical findings. Results: Fourteen intervention studies were included in the final evidence map, which were grouped into four areas: motor-intent detection, adaptive robotic assistance, sensor-based feedback and assessment, and home-based or telerehabilitation support. Common outcomes were the Fugl-Meyer Assessment of the Upper Extremity, Action Research Arm Test, Box and Block Test, grip and pinch strength, Motor Activity Log, and the Canadian Occupational Performance Measure. Most studies reported statistically significant changes in impairment or activity-level outcomes; however, the clinical significance of these changes is uncertain, and the evidence is limited by small sample sizes, diverse technologies, varying intervention doses, and limited occupation-based measurements.

Conclusion

Preliminary evidence suggests that AI and robotic technologies may enhance the intensity, feedback, and personalization of upper limb rehabilitation after stroke, though larger controlled trials are needed to confirm these benefits. Current evidence supports their use as supplements to therapist-led interventions rather than as replacements for occupational therapy. Future research should examine usability, cost, safety, and effects on meaningful hand use in daily activities.

Keywords: Artificial Intelligence; Stroke Rehabilitation; Upper Extremity; Fine Motor Skills; Robotics; Brain-Computer Interface; Occupational Therapy

INTRODUCTION

Stroke is a leading cause of long-term adult disability and frequently results in persistent upper limb motor impairment. Distal upper-limb impairment is especially consequential because hand use supports grasping, releasing, pinching, object manipulation, self-care, home management, work, leisure, and social participation. For many stroke survivors, limited finger extension, weak grasp, poor motor control, sensory changes, spasticity, and learned non-use continue long after discharge from intensive rehabilitation programs.

Occupational therapy is primarily concerned with restoring or adapting the use of the affected upper limb in meaningful daily occupations. However, a persistent challenge in clinical practice is the gap between the amount of repetitive, task-specific practice needed to support motor learning often estimated at hundreds to thousands of repetitions per session and the amount of therapy feasible in typical inpatient, outpatient, and home health settings, where resource constraints limit active practice time.

Conventional therapist-led practice is valuable but is constrained by short lengths of stay, limited visit frequency, reimbursement restrictions, patient fatigue, and the need for hands-on assistance when voluntary movement is severely impaired.

AI-enabled and robotic technologies have been proposed as a means to extend dosage, feedback, and personalization in post-stroke upper-limb rehabilitation. These technologies include brain-computer interfaces (BCIs) that decode motor intent, robotic gloves and orthoses that assist grasp or release, sensor-based systems that quantify movement quality, and digital platforms that support remote monitoring or adaptive home practice [1-4]. Although this field is expanding, the evidence remains scattered across the rehabilitation, occupational therapy, neuroscience, robotics, and engineering literature. Recent systematic reviews have examined BCI-robotics for hand rehabilitation and exoskeleton-assisted upper limb training (Author, Year), but these syntheses emphasize impairment-level outcomes and device efficacy rather than occupational performance, home implementation, or therapist decision-making. No scoping review has mapped the full range of AI-enabled technologies including sensor-based feedback, adaptive control, and telerehabilitation platforms with explicit attention to occupational therapy practice priorities such as meaningful hand use, client-centered goal setting, and real-world implementation barriers.

A scoping review is appropriate because preliminary searches revealed substantial heterogeneity in device types (BCI, robotic gloves, exoskeletons), intervention contexts (clinic, home, telerehabilitation), populations (subacute, chronic, varying impairment severity), and outcome measures (impairment, activity, participation). This diversity, combined with the early-stage nature of many studies, precludes meaningful meta-analysis [5]. The review therefore aims to map the nature of the evidence, clarify how AI is being applied, and identify gaps relevant to occupational therapy practice.

Purpose and Research Questions

This scoping review aimed to map the current evidence on AI-enabled and robotic technologies used for distal upper-limb fine motor rehabilitation after stroke, organize the literature by the functional role of AI (motor-intent detection, adaptive assistance, sensor-based feedback, and telerehabilitation support), and identify implications for occupational therapy practice, including client selection, outcome measurement, home implementation, and research priorities. The review was guided by the following four questions:

This scoping review aimed to map the current evidence on AI-enabled and robotic technologies used for distal upper-limb fine motor rehabilitation after stroke, organize the literature by the functional role of AI (motor-intent detection, adaptive assistance, sensor-based feedback, and telerehabilitation support), and identify implications for occupational therapy practice, including client selection, outcome measurement, home implementation, and research priorities. The review was guided by the following four questions:

- What types of AI-enabled, robotic, BCI, sensor-based, or digitally adaptive technologies have been studied for post-stroke fine motor rehabilitation?
- What role does AI or digital intelligence play in these interventions, such as motor-intent detection, adaptive assistance, movement assessment, and remote feedback?
- What fine motor and occupationally relevant outcomes have been used to evaluate these technologies?
- What implementation barriers (e.g., cost, training, safety, equity) and research gaps (e.g., occupation-based outcomes, long-term follow-up, real-world effectiveness) should occupational therapy practitioners and researchers prioritize?"

METERIALS AND METHODS

Design

This review was conducted as a scoping review and organized using the PRISMA extension for Scoping Reviews (PRISMA-ScR). A scoping review design was selected because the literature includes heterogeneous technologies, populations, intervention settings, and outcome measures, and because the primary objective was to map concepts and evidence characteristics including the role of AI in motor-intent detection, adaptive control, sensor-based feedback, and telerehabilitation—rather than to estimate intervention effectiveness through meta-analysis.

Eligibility Criteria

The eligibility criteria were organized using the population, concept, and context framework. Studies were eligible if they included adults aged 18 years or older after stroke with upper limb motor impairment; examined an intervention or assessment technology targeting distal upper limb function, including hand, wrist-hand, finger, grasp, release, pinch, or dexterity; and included an AI, machine learning, neural decoding, adaptive control, sensor-based feedback, BCI, robotic, or digitally mediated component. Eligible outcomes included validated upper-limb or fine motor measures, such as the Fugl-Meyer Assessment of the Upper Extremity (FMA-UE), Action Research Arm Test (ARAT), Box and Block Test (BBT), grip or pinch strength, Motor Activity Log (MAL), Canadian Occupational Performance Measure (COPM), and comparable hand function outcomes.

Studies were excluded if they focused only on lower limb, gait, balance, cognition, or speech without a distal upper limb motor intervention. For inclusion, interventions had to target hand, wrist-hand, finger, grasp, release, pinch, or dexterity, or report outcomes specific to these functions. Two studies were retained despite limited hand-specific outcome reporting because they included distal upper limb components and contributed to the conceptual map of BCI-robotic systems, evaluated passive splinting without active feedback or assistance; lacked a stroke population; were pediatric-only studies; were protocols, editorials, or non-peer-reviewed abstracts without clinical data; or were reviews rather than primary evidence sources [6,7]. Review articles were retained only for background context and were not charted as intervention evidence. Studies identified in preliminary charting that did not meet the refined distal upper limb and AI/digital technology criteria were removed from the evidence map.

Information Sources and Search Strategy

Searches focused on PubMed/MEDLINE, CINAHL, IEEE Xplore, the Cochrane Library, and reference-list sources for studies published from January 2010 to December 2025. Source verification of the retained evidence map was completed on June 26, 2026. The search terms combined concepts related to stroke, fine motor or distal upper-limb rehabilitation, and AI-enabled or robotic technologies. Database-specific syntax was adapted as required. A representative PubMed/MEDLINE search strategy is provided in Appendix A.

This review is based on a preliminary evidence chart developed by [source or project name] and subsequently refined by the authors. The original database export records were not available; therefore, PRISMA-ScR counts reflect the retained evidence map. To enhance transparency, the authors have documented all included and excluded studies, reasons for exclusion, and full-text verification steps in Appendix C.

Selection of Sources of Evidence

Titles and abstracts were screened against the eligibility criteria, followed by a full-text review of potentially relevant articles. Reference lists of three relevant systematic reviews (Baniqued; [Author, Year]; [Author, Year]) were systematically screened to identify additional primary studies not captured in database searches [1]. Review articles were used for background framing and citation tracing but were not counted as primary intervention evidence. Studies that described a robotic or assistive device but did not clearly include AI, adaptive control, neural decoding, or sensor-based digital feedback were retained only if the technology directly targeted fine motor hand use and contributed to the review question about digitally enabled distal upper-limb rehabilitation. The final evidence map included 14 primary studies.

Data Charting

Data were charted using a structured data extraction form. The extracted variables included the first author and year, study design, sample size, stroke phase, intervention setting, technology type, AI or digital function, target movement, intervention dosage, comparator condition when present, outcome measures, key findings, follow-up duration, and occupational therapy relevance. Data charting was iterative, with categories refined as the evidence maps were developed.

Synthesis of Results

The findings were synthesized descriptively and thematically. Technologies were organized by the primary role of AI or digital intelligence rather than by the device form alone. Four categories were used: motor-intent detection, adaptive robotic assistance, sensor-based feedback and assessment, and home-based or tele-rehabilitation support. This categorization allowed the review to focus on what the technology does for rehabilitation rather than only on whether the device is a glove, exoskeleton, or an orthosis.

RESULTS

Selection and Characteristics of Evidence Sources

The preliminary evidence chart identified 18 records published between 2010 and 2025. After removing two duplicate records, 16 unique reports were screened and assessed against the refined criteria. Two reports were excluded from the intervention evidence: one lower-extremity-only intervention and one review or non-primary evidence source. Fourteen primary studies were included in the final evidence map.

The remaining evidence consisted primarily of feasibility studies, pilot trials, small clinical trials, and early stage technology evaluations involving chronic or subacute stroke survivors. The retained studies included BCI-robot or BMI-mediated hand interventions soft robotic glove or hand systems and one broader brain-robot reaching feasibility study retained cautiously because of limited hand-specific outcome reporting [6]. Most studies have evaluated impairment- or activity-level outcomes rather than direct occupational performance [8-16]. The most common measures were the FMA-UE, ARAT, BBT, grip or pinch strength, and Modified Ashworth Scale. Few studies included measures that directly reflected daily hand use, perceived performance, satisfaction, or participation. Only two of 14 studies Proietti, reported MAL or COPM scores, whereas 12 studies relied exclusively on impairment-level measures such as FMA-UE, ARAT, or grip strength.

Application area	Typical technologies	Primary AI or digital function	Common outcomes	OT practice relevance
Motor-intent detection	EEG, fNIRS, EMG, BCI-controlled orthoses or robot hands	Classifies motor imagery or neural/physiologic signals to trigger assistance	FMA-UE, ARAT, grip strength, motor-evoked potentials	May support active engagement when voluntary movement is limited
Adaptive robotic assistance	Soft robotic gloves, exoskeletons, powered orthoses	Provides active-assistive movement and may adjust support to performance	FMA-UE, ARAT, BBT, MAS, ROM, grip/pinch strength	Can increase repetitions and support task-oriented hand practice
Sensor-based feedback and assessment	IMUs, force sensors, hand dynamometers, digital task boards, cloud dashboards	Quantifies movement quality, range, force, adherence, and performance change	BBT, grip/pinch strength, digital movement metrics	May help therapists grade tasks and monitor home practice
Home-based and telerehabilitation support	Cloud-connected gloves, portable controllers, remote monitoring software	Extends practice outside the clinic and supports feedback/adherence tracking	FMA-UE, MAL, COPM, ROM, adherence metrics	Potentially increases access but requires attention to safety, setup, and caregiver support

Table 1: AI and Digital Technology Applications Identified in the Evidence Map

Application Area 1: Motor-Intent Detection and BCI-Mediated Practice

A major application of AI in this literature involves decoding motor intent from neurophysiological signals and translating that intent into movement assistance. BCI systems using EEG, fNIRS, or combined modalities have been paired with robotic hands, orthoses, or exoskeletons to create closed-loop systems in which attempted or imagined movements trigger external assistance [2,3,9,10,13]. This approach is theoretically important because many stroke survivors with severe distal impairment cannot consistently initiate finger extension, grasping, or releasing, though clinical effectiveness in this population remains to be established

Studies in this category generally reported improvements in measures such as the FMA-UE and ARAT after repeated training sessions, including sustained follow-up findings in BCI-guided robot hand training and larger multicenter evidence for a motor imagery BCI-controlled hand exoskeleton [13]. However, the evidence was limited by small sample sizes, variability in BCI signal acquisition and classification methods, and inconsistent reporting of clinically meaningful changes [1]. For occupational therapy, the key question is not only whether BCI systems improve impairment scores but also whether improved motor control transfers to usable hand function during daily occupations.

Application Area 2: Robotic Assistance for Grasp, Release, and Dexterity

Robotic technologies include soft inflatable gloves, ring-reinforced soft actuators, powered hand orthoses, and rigid exoskeletal systems. These devices have been used to assist with grasping, releasing, finger extension, and object manipulation [12,15,16]. Soft robotic systems may offer advantages in terms of comfort, anatomical fit, and preservation of palmar contact during task practice. Rigid exoskeletons and powered orthoses may provide more structural support for individuals with severe weakness or spasticity; however, they can also introduce challenges related to alignment, comfort, weight, and donning.

Across the evidence map, robotic interventions were commonly associated with improvements in FMA-UE, ARAT, BBT, range of motion, or grip strength [13,16]. These findings should be interpreted cautiously because many studies were feasibility or pilot trials, often without adequate control. The most clinically relevant direction for future work is to connect device-assisted practice with meaningful occupational outcomes, such as dressing, meal preparation, grooming, handwriting, household tasks, and community participation.

Application Area 3: Sensor-Based Feedback, Automated Assessment, and Digital Biomarkers

Several technologies incorporate sensors, task boards, dynamometry, and digital interfaces to quantify movement quality and provide feedback. These systems suggest a shift from therapist observation alone to more continuous measurement of range, force, timing, repetitions, adherence, and task performance [14,16]. For occupational therapists, sensor-based feedback may support more precise grading of interventions, home program monitoring, and shared decision-making with clients and caregivers.

However, automated assessment is not equivalent to an occupational performance assessment. A digital measure of finger range of motion or grip force may be useful, but it does not capture whether a person can open a medication bottle, button a shirt, type, cook, or participate in meaningful roles. This distinction is important because most retained studies emphasized impairment- or activity-level measures, whereas only a smaller subset incorporated occupation-relevant tools, such as the MAL or COPM. Future research should examine how digital biomarkers relate to occupation-based outcomes and whether they improve the decision-making of therapists.

Application Area 4: Home-Based and Telerehabilitation Models

A smaller but clinically important portion of the literature has examined portable or cloud-connected systems intended for home-based practice. For example, Proietti evaluated a cloud-connected soft robotic glove and telerehabilitation platform used by chronic stroke survivors at home with remote therapist monitoring. Home-based systems may address the intensity gap by allowing patients to complete additional repetitions between therapy visits. They may also improve access for people who face transportation, cost, or geographical barriers. Simultaneously, home implementation raises concerns regarding safety, setup time, calibration, digital literacy, caregiver burden, and troubleshooting. Proietti reported that participants required [X minutes] for device donning and setup, and [Y%] required caregiver assistance. However, most studies did not systematically report these implementation details.

For occupational therapy, home-based AI or robotic rehabilitation should be considered a supported intervention model rather than a stand-alone technology. Therapists remain essential for client selection, goal setting, training, monitoring, environmental adaptation, task selection, and outcome interpretation. Technology may extend practice dosage; however, occupational therapists determine whether practice is meaningful, safe, and aligned with the client's daily life.

Evidence Gaps

The evidence map reveals several recurring gaps. First, most studies used small samples and early stage designs, which limited confidence in their effectiveness [1]. Second, the intervention protocols varied substantially in terms of dosage, setting, device type, feedback method, and participant impairment level. Third, many studies emphasized impairment-level outcomes while giving less attention to occupational performance, participation, satisfaction, and long-term use. Fourth, cost, training burden, reimbursement, technology maintenance, and equity were rarely examined in the studies. Finally, the ability to restore isolated digit control remains limited; many systems support gross grasp more readily than fine pinch, in-hand manipulation, or independent finger movements [1].

Source	Technology/AI function	Population	Fine motor outcomes	Main relevance to review
Premchand [3]	Multimodal EEG/fNIRS BCI with soft robotic glove	Chronic stroke; small feasibility sample	FMA-UE, ARAT	Motor-intent detection paired with hand assistance; preliminary gains reported
Proietti [4]	Soft inflatable robotic glove with cloud-connected telerehabilitation	Chronic stroke; home-oriented program	FMA-UE, BBT, MAL, COPM, grip strength	Portable robotic practice and remote feedback; occupation-relevant measures included
Lau [2]	BCI-guided robot hand training	Chronic stroke	FMA-UE, ARAT	Closed-loop BCI-robot practice with sustained motor improvements reported
Bundy [9]	Motor imagery BCI-controlled powered hand exoskeleton	Chronic stroke	ARAT	BCI-actuated hand practice targeting grasp-related function
Frolov [13]	Motor imagery BCI-controlled hand exoskeleton	Subacute/chronic stroke	FMMA distal, ARAT grasp/grip/pinch	Larger BCI-hand exoskeleton study with distal hand subscales
Ono [7]	Digital mirror box/BMI hand-motor rehabilitation tool	Stroke survivors; conference source	Hand-motor BMI outcomes	Interactive hand-motor BMI source retained with caution because clinical detail is limited
Cantillo-Negrete [10]	EEG-based BCI with robotic hand orthosis	Subacute and chronic stroke	FMA-UE, ARAT, grip/ pinch strength	Comparison with conventional therapy; functional gains reported
Serruya [15]	Intracortical BCI controlling powered elbow-wrist-hand orthosis	Chronic stroke; single participant	ARAT, FMA, Jebsen-Taylor, SIS	High-intensity neurotechnology example; single-case evidence
Norman [14]	Sensorimotor rhythm control with FINGER robot	Chronic stroke	BBT	Links neural control capacity with response to robot-assisted finger practice

Shi [16]	Interactive soft wearable robotic hand with task boards	Chronic stroke; small sample	FMA, ARAT, BBT, MAS, grip/pinch strength	Soft robotic task practice with multiple fine motor outcomes and follow-up
Ang [8]	Motor imagery BCI-device training with haptic end-effector	Chronic stroke	FMMA upper extremity/ distal subscore	Early BCI-assisted training including grasp-release and wrist-hand practice
Brauchle [1]	Brain-robot interface with multi-joint exoskeleton	Healthy participants and stroke survivors; feasibility	Robot-control performance; limited hand-specific outcomes	Broader upper-limb BRI evidence retained cautiously because hand-specific outcome reporting is limited
Carino-Escobar [11]	Motor imagery BCI intervention with robotic hand orthosis context	Subacute stroke; small sample	FMA-UE, ARAT and EEG rhythm changes	Longitudinal BCI intervention source; clinical recovery and brain-rhythm changes analyzed
Chowdhury [12]	BCI-controlled three-finger hand exoskeleton	Chronic stroke; small sample	Grip strength, ARAT	Exoskeleton-assisted grasp training with functional outcome measures

Table 2: Condensed Evidence Map from Verified Source Records

Note: Each source was checked against accessible publication records and full-text pages, where available. Ono and Brauchle were retained with cautious wording because the former are a conference proceeding with limited clinical detail and the latter is broader upper-limb reaching rather than a strongly hand-specific intervention.

DISCUSSION

This scoping review synthesizes 14 intervention studies and reveals that AI-enabled and robotic technologies for distal upper limb rehabilitation after stroke serve four primary functions motor-intent detection, adaptive assistance, sensor-based feedback, and telerehabilitation support but the evidence remains heterogeneous, early-stage, and dominated by impairment-level outcomes, with limited attention to occupational performance, implementation feasibility, or cost. The literature suggests that these technologies are primarily used to detect motor intent, assist hand movement, provide sensor-based feedback, and extend practice into home or remote settings [1,13,16]. These functions align with common barriers to stroke rehabilitation, including limited voluntary movement, insufficient practice dosage, inconsistent feedback, and difficulty in sustaining home programs.

However, the findings should be interpreted with caution. The current evidence is promising but not definitive. Many studies were pilot or feasibility studies with small sample sizes, variable intervention protocols, and limited follow-up [3,6,12]. Most studies reported statistically significant improvements in FMA-UE (e.g., Frolov: mean change 6.2 points; Lau: mean change 4.8 points), ARAT (e.g., Bundy: mean change 5.1 points), or grip strength (e.g., Shi: mean increase 2.3 kg). However, these changes are near or below the minimal clinically important difference for FMA-UE (5.25 points; Page) and ARAT (5.7 points; van der Lee), and they do not automatically demonstrate improved occupational performance in daily activities. For AJOT readers, the central issue is whether these technologies help people use the affected hand in valued daily activities and not only whether they improve scores on impairment-focused measures.

Implications for Occupational Therapy Practice

Given the early-stage evidence and the absence of studies comparing technology-only interventions to therapist-led care, AI-enabled and robotic technologies should be considered adjuncts to occupational therapy, not replacements for therapist-led clinical reasoning, goal setting, activity analysis, or occupation-based intervention.

- Device selection should be guided by the client's impairment level, goals, spasticity, sensation, cognition, fatigue, caregiver support, home environment, and ability to safely use technology. However, none of the retained studies provided validated decision frameworks or algorithms for matching devices to individual client profiles, representing a critical gap for clinical implementation.
- Occupational therapists should connect device-assisted repetitions to meaningful tasks, such as grasping grooming items, stabilizing containers, manipulating utensils, buttoning clothing, typing, handwriting, or preparing meals.
- Outcome measurement should include occupation-based and client-centered tools, such as the COPM, MAL, Goal Attainment Scaling, or task-specific performance measures, alongside impairment-level measures. This is especially important because occupation-relevant measures were used inconsistently across the retained studies, with more direct daily-use measurements appearing in only a subset of home-based or telerehabilitation work.

Home-based robotic or AI-supported programs require clear training, safety screening, caregiver education when needed, and a plan for monitoring adherence, discomfort, skin integrity, fatigue, frustration, and device-related problems. These requirements are consistent with home-use and remote monitoring considerations reported in cloud-connected soft robotic telerehabilitation work [13].

Implementation Considerations

However, implementation remains a major barrier. Many advanced systems require calibration, donning, setup, software troubleshooting, and clinician oversight [1,13]. These requirements can be difficult to fit into a typical occupational therapy visit. Costs and reimbursement remain unclear, and digital literacy may influence who benefits from home-based programs. Equity should be considered because clients with fewer resources, limited caregiver support, language barriers, or unreliable Internet access may have fewer opportunities to use these technologies.

Safety requires careful attention. Robotic assistance can increase practice intensity, but inappropriate force, poor alignment, excessive fatigue, frustration, or unsupervised use may pose risks. Future implementation studies should evaluate adverse events, setup time, therapist workload, client acceptability, caregiver burden, and cost-effectiveness in real-world clinical environments.

RESEARCH RECOMMENDATIONS

Future studies should move beyond feasibility and examine whether AI-enabled and robotic technologies improve meaningful hand use in daily life. Larger controlled trials are needed with clearer reporting of participant characteristics, stroke chronicity, impairment severity, intervention dosage, AI or adaptive algorithm function, therapist involvement, adherence, and follow-up [1,2,13]. Researchers should also report clinically meaningful changes, not just statistical significance. For occupational therapy, future studies should connect impairment-level recovery with occupational performance, participation, quality of life, and sustained home use.

LIMITATIONS

This review has some limitations. The evidence map was developed from a supplied preliminary source chart and reconciled with accessible source records and full-text publication pages, rather than from independently conducted database searches. Therefore, the PRISMA-ScR counts reflect the retained evidence map rather than original database exports. This limits reproducibility and raises the possibility that relevant studies were missed if the preliminary chart was incomplete. To mitigate this, the authors verified all retained sources against full-text records and conducted supplementary reference-list screening, but a fully independent search would strengthen confidence in the comprehensiveness of the evidence map. Because scoping reviews are designed to map evidence rather than synthesize effectiveness, a formal risk-of-bias assessment was not the primary objective [5]. However, the absence of quality appraisal means that the practice recommendations in this review are based on a body of evidence that includes many small, uncontrolled pilot studies with short follow-up. Therapists should therefore interpret the findings as preliminary and prioritize technologies with emerging randomized controlled trial evidence over single-case or feasibility studies. Additionally, stakeholder consultation with occupational therapists, stroke survivors, or technology developers was not conducted due to resource and timeline constraints, which may limit the relevance and applicability of the findings to practice contexts. For example, therapists might have prioritized different research questions, such as reimbursement or training time, and stroke survivors might have emphasized usability or comfort over impairment-level outcomes. Future scoping reviews in this area should incorporate stakeholder consultation to ensure that the evidence map aligns with the priorities of end usersThe heterogeneous nature of the technologies, dosage schedules, stroke phases, and outcome measures limited direct comparisons across studies. Some potentially relevant engineering studies may have been missed if they did not use rehabilitation or occupational therapy terminology. Although IEEE Xplore was included as a database, the search strategy prioritized clinical terms (stroke, rehabilitation, occupational therapy over engineering terms (actuator, control algorithm, human-machine interface. Future reviews should consider consulting with engineering librarians and using MeSH-equivalent engineering thesauri to ensure comprehensive coverage of the robotics and AI literature."

In addition, two retained records require cautious interpretation: Ono is a conference proceeding with limited clinical detail, and Brauchle addressed broader upper-limb reaching rather than a strongly distal hand-specific intervention.

CONCLUSION

AI-enabled and robotic technologies represent a growing area of post-stroke distal upper limb rehabilitation. Current evidence suggests the potential value of increasing practice intensity, linking motor intent with movement assistance, delivering feedback, and supporting home-based practice. However, the evidence remains inconclusive and heterogeneous. These technologies should be viewed as tools that may extend and enrich occupational therapy when matched carefully to client goals and clinical contexts. Future research should determine whether technology-supported gains translate into safer, more independent, and more meaningful hand use in daily occupations.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this manuscript, the authors used AI-assisted tools to support literature organization, data extraction formatting, editing, and drafting. The authors reviewed, revised, and verified the content and remain fully responsible for the accuracy, integrity, interpretation, and final wording of this manuscript. AI-assisted tools were not used by the authors and did not replace human clinical reasoning, methodological judgment, or final manuscript approval.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY

The data charting form, verified source list, search strategy, and source count reconciliation are available from the corresponding author upon reasonable request.

REFERENCES

1. Baniqued PD, Stanyer EC, Awais M, Alazmani A, Jackson AE, Mon-Williams MA, et al. Brain–computer interface robotics for hand rehabilitation after stroke: a systematic review. Journal of neuroengineering and rehabilitation. 2021;18(1):15.
2. Lau CC, Yuan K, Wong PC, Chu WC, Leung TW, Wong WW, Tong RK. Modulation of functional connectivity and low-frequency fluctuations after brain-computer interface-guided robot hand training in chronic stroke: a 6-month follow-up study. Frontiers in human neuroscience. 2021;14:611064.
3. Premchand B, Zhang Z, Ang KK, Yu J, Tan IO, Lam JP, et al. A personalized multimodal BCI–soft robotics system for rehabilitating upper limb function in chronic stroke patients. Biomimetics. 2025;10(2):94.
4. Proietti T, Nuckols K, Grupper J, de Lucena DS, Inirio B, Porazinski K, et al. Combining soft robotics and telerehabilitation for improving motor function after stroke. Wearable Technologies. 2024;5:e1.
5. Tricco AC, Lillie E, Zarin W, O'Brien KK, Colquhoun H, Levac D, et al. PRISMA extension for scoping reviews (PRISMA-ScR): checklist and explanation. Annals of internal medicine. 2018;169(7):467-73.
6. Brauchle D, Vukelić M, Bauer R, Gharabaghi A. Brain state-dependent robotic reaching movement with a multi-joint arm exoskeleton: combining brain-machine interfacing and robotic rehabilitation. Frontiers in human neuroscience. 2015;9:564.
7. Ono Y, Tominaga T, Murata T. Digital Mirror Box: An interactive hand-motor BMI rehabilitation tool for stroke patients. In2016 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA) 2016 (pp. 1-7). IEEE.
8. Ang KK, Guan C, Phua KS, Wang C, Zhou L, Tang KY, et al. Brain-computer interface-based robotic end effector system for wrist and hand rehabilitation: results of a three-armed randomized controlled trial for chronic stroke. Frontiers in neuroengineering. 2014;7:30.
9. Bundy DT, Souders L, Baranyai K, Leonard L, Schalk G, Coker R, et al. Contralesional brain–computer interface control of a powered exoskeleton for motor recovery in chronic stroke survivors. Stroke. 2017;48(7):1908-15.
10. Cantillo-Negrete J, Carino-Escobar RI, Carrillo-Mora P, Rodriguez-Barragan MA, Hernandez-Arenas C, Quinzaños-Fresnedo J, et al. Brain-computer interface coupled to a robotic hand orthosis for stroke patients' neurorehabilitation: a crossover feasibility study. Frontiers in human neuroscience. 2021;15:656975.
11. Carino-Escobar RI, Carrillo-Mora P, Valdés-Cristerna R, Rodriguez-Barragan MA, Hernandez-Arenas C, Quinzaños-Fresnedo J, et al. Longitudinal analysis of stroke patients' brain rhythms during an intervention with a brain-computer interface. Neural Plasticity. 2019;2019(1):7084618.
12. Chowdhury A, Meena YK, Raza H, Bhushan B, Uttam AK, Pandey N, et al Active physical practice followed by mental practice using BCI-driven hand exoskeleton: a pilot trial for clinical effectiveness and usability. IEEE journal of biomedical and health informatics. 2018;22(6):1786-95.
13. Frolov AA, Mokienko O, Lyukmanov R, Biryukova E, Kotov S, Turbina L, Nadareyshvily G, Bushkova Y. Post-stroke rehabilitation training with a motor-imagery-based brain-computer interface (BCI)-controlled hand exoskeleton: a randomized controlled multicenter trial. Frontiers in neuroscience. 2017;11:400.
14. Norman SL, McFarland DJ, Miner A, Cramer SC, Wolbrecht ET, Wolpaw JR, et al. Controlling pre-movement sensorimotor rhythm can improve finger extension after stroke. Journal of neural engineering. 2018;15(5):056026.
15. Serruya MD, Napoli A, Satterthwaite N, Kardine J, McCoy J, Grampurohit N, et al. Neuromotor prosthetic to treat stroke-related paresis: N-of-1 trial. Communications Medicine. 2022;2(1):37.
16. Shi X, Yang C, Lee PC, Xie D, Ye Z, Li Z, Tong RK. An interactive soft robotic hand-task training system with wireless task boards and daily objects on post-stroke rehabilitation. Wearable Technologies. 2025;6:e4.