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A Systematic Review and Critical Analysis of Vision-Based and Wearable Sensor Technologies for Hand Rehabilitation in Stroke Survivors

Kamal[1] | Debanga Raj Neog[1] | M. K. Bhuyan[1,2] | Karl F. MacDorman[3] | Ram Kumar Karsh[4] | Rabul Hussain Laskar[4]

[1]Mehta Family School of Data Science and Artificial Intelligence, Indian Institute of Technology Guwahati, Guwahati, Assam, India | [2]Department of Electronics and Electrical Engineering, Indian Institute of Technology Guwahati, Guwahati, Assam, India | [3]Luddy School of Informatics, Computing, and Engineering, Indiana University, Indianapolis, Indiana, USA | [4]Department of Electronics and Communication Engineering, National Institute of Technology, Silchar, Assam, India

Correspondence: Kamal (kkamal@iitg.ac.in)

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ABSTRACT

Stroke is a leading cause of long-term disability, with 80% of survivors experiencing acute upper-limb impairment. Although vision-based and wearable sensor technologies have the potential to improve rehabilitation, a thorough analysis of their comparative advantages, technical limitations and clinical readiness is still lacking. This systematic review provides a methodologically rigorous analysis of the peer-reviewed literature from 2005 to 2025, synthesising and critically evaluating vision-based and wearable sensor technologies for post-stroke hand rehabilitation. Following PRISMA guidelines, we searched PubMed, Scopus and Web of Science. We analysed 132 included studies to identify a trend towards deep learning-based computer vision and hybrid wearable systems. However, quantitative synthesis exposed critical gaps: technical benchmarks (e.g., latency and computational cost) were reported in fewer than 5% of studies, and the median sample size was only 17 participants. Methodological quality was low to moderate, with only 12% of studies being randomised controlled trials. We present a new taxonomy classifying systems by sensing modality and maturity, which reveals a lab-to-clinic gap. Although innovation is rapid, a lack of standardised benchmarking hinders clinical translation. We propose a decision-making framework to guide future research and implementation.

1 | Introduction

Stroke is a leading cause of disability worldwide, affecting over 17 million individuals annually [1]. It frequently leads to permanent impairments that severely hinder everyday functions, including speaking, walking and thinking. Impairments in hand and arm function are among the most prevalent and severe deficits following a stroke. It limits independence and quality of life by affecting activities of daily living (ADL), such as eating, dressing and personal hygiene [2–4]. By restoring or improving upper-limb function through structured therapeutic interventions, such as motor recovery therapies, sensory re-education, compensatory strategies and targeted exercises, hand rehabilitation plays a critical role in post-stroke recovery [5–7]. Restoring hand function improves the quality of life for stroke survivors and reduces caregiver strain by enabling them to perform everyday tasks independently. Secondary complications such as muscle weakness, joint deformities and contractures are also mitigated by rehabilitation [8, 9]. Furthermore, hand rehabilitation leverages the brain's capacity to reorganise by forming new neural connections, facilitating recovery through consistent and targeted

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exercise [10, 11]. Months or even years after a stroke, functional recovery can be improved with early and intensive rehabilitation [12]. Virtual reality (VR) and robotic-assisted therapies are two examples of how technological advancements have increased the potential for hand rehabilitation [13]. They provide embodied or immersive interventions to encourage stroke survivors in performing repetitive, intense therapeutic exercise [5, 6]. Although technology increasingly aids this recovery, existing reviews (e.g., Laver et al. [14]) predominantly focus on clinical outcomes (e.g., FMA scores). There is a significant unmet need for a review that critically evaluates computer vision architectures, such as the shift from convolutional neural networks (CNNs) to transformers, and provides technical benchmarking (e.g., latency and resistance to occlusion) of these technologies. This review addresses that gap.

1.1 | Historical Context

Hand rehabilitation has evolved significantly from the foundational mechanical interventions of the mid-20th century. As depicted in Figure 1, the field progressed to robotic devices for precise motion exercises in the early 2000s (represented by landmark studies, such as Krebs et al. [15]). This was followed by the development of wearable smart gloves in the 2010s [16] and the integration of virtual reality around 2015 [17]. The current era (2020s) is defined by AI-driven personalisation and markerless vision-based monitoring using deep learning architectures, such as Swin3D [18] and topology-aware transformers [19].

1.2 | Paper Organisation

The remainder of this paper is organised as follows. Section 2 details the PRISMA-based methodology. Section 3 presents the quantitative synthesis of the 132 studies, including technical benchmarking. Section 4 provides a critical technical analysis of computer vision architectures. Section 5 reviews state-of-the-art systems, categorising them by modality (vision vs. wearable). Section 6 outlines broader clinical applications and underlying technologies. Section 7 discusses the lab-to-clinic gap and presents a decision-making framework. Finally, Section 8 concludes the paper.

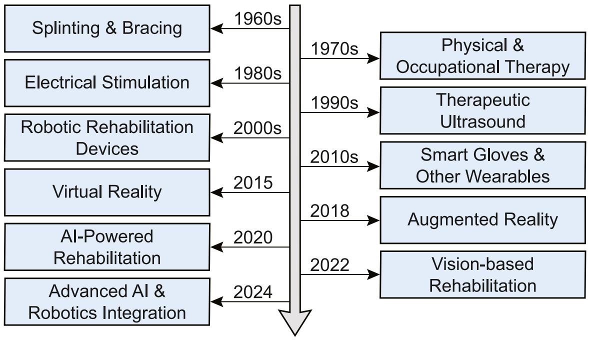

FIGURE 1 | Timeline representing the evolution of hand rehabilitation technologies for stroke from traditional methods of splinting and bracing to modern AI-driven vision systems.

2 | Methods

This systematic review was designed and conducted in strict accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines [20].

2.1 | Search Strategy and Data Sources

We conducted a comprehensive search of the peer-reviewed literature across three major databases: PubMed, Scopus and Web of Science. The search covered the period from January 2005 to January 2025. To ensure reproducibility, we employed specific combinations of Medical Subject Headings (MeSH) and keywords related to stroke, hand rehabilitation and technology. Table 1 details the exact search strings used.

2.2 | Study Selection and Quality Assessment

The selection process followed the PRISMA flow diagram (Figure 2). Of the 60,580 records identified, duplicate records were removed using Rayyan ($n = 30,000$), and records published before 2005 were excluded. Two independent reviewers (K. and D.R.N.) screened the remaining records for eligibility ($\kappa = 0.85$, indicating strong agreement). Disagreements were resolved through discussion or adjudication by a third reviewer (M.K.B.). A total of 120 reports were not retrieved for full-text assessment. These exclusions primarily comprised conference abstracts without full papers (65%), nonpeer-reviewed dissertations or theses (25%) and articles unavailable in English (10%). Adhering to these exclusion criteria ensured that only rigorously peer-reviewed, reproducible studies were included in the final synthesis. Methodological quality was assessed using the PEDro scale for randomised controlled trials (RCTs) and the Downs and Black checklist for nonrandomised studies. Studies were categorised as high quality (PEDro ≥ 6), fair or poor.

2.3 | Data Extraction and Synthesis

Data were extracted into a standardised format that captured study design, sample size, sensor modality, computer vision architecture (e.g., CNN vs. transformer), dataset used (public vs. private) and key performance metrics. We performed a qualitative synthesis of technical architectures and a quantitative

TABLE 1 | Search strategy and keywords.

Database	Search string/keywords
PubMed	(((“Stroke”[Mesh]) OR “stroke survivor”) AND ((“Hand”[Mesh]) OR “hand function”) AND ((“Rehabilitation”[Mesh]) OR “occupational therapy”)) AND ((“computer Vision”[Mesh]) OR “vision-based” OR (“Wearable Electronic Devices”[Mesh]) OR “wearable sensor” OR “smart glove” OR “virtual reality”)
Scopus	(TITLE-ABS-KEY(Stroke) AND TITLE-ABS-KEY(Hand rehabilitation) AND (TITLE-ABS-KEY(Computer vision) OR TITLE-ABS-KEY (Wearable) OR TITLE-ABS-KEY(Robotics)))
Web of Science	TS = (“Stroke” AND “hand rehabilitation” AND (“computer vision” OR “wearable sensor” OR “deep learning”))

synthesis of reported system latencies and accuracies, where comparable data were available.

3 | Results: Quantitative Synthesis

3.1 | Study Characteristics

A total of 132 studies met the inclusion criteria. The trends in publications over the years are illustrated in Figure 3, showing a sharp increase in vision-based research after 2015, likely driven by the maturation of deep learning frameworks.

3.2 | Quality of Evidence

Based on our quality assessment (Table 2), 12% of the included studies were RCTs, whereas 55% were proof-of-concept or feasibility studies with sample sizes less than 20. The lack of RCTs highlights a substantial lab-to-clinic gap in the literature.

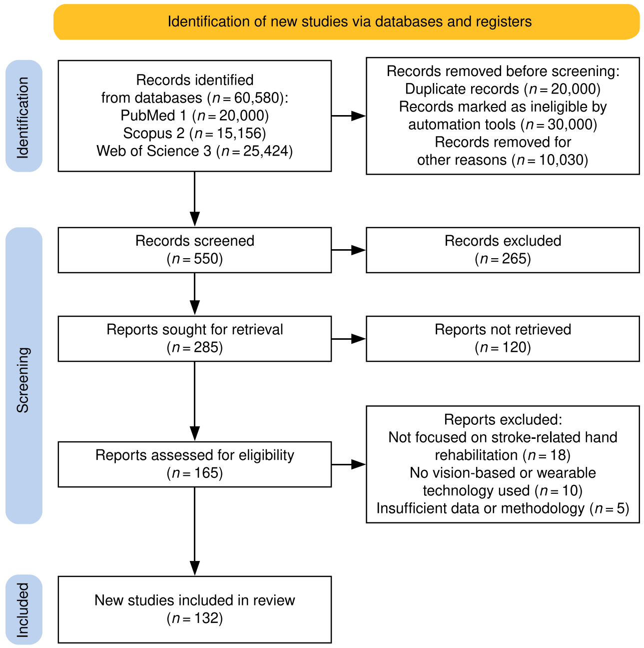

FIGURE 2 | PRISMA flow diagram for the study selection process. The 120 reports not retrieved primarily consisted of conference abstracts and dissertations that did not meet the peer-review inclusion criteria.

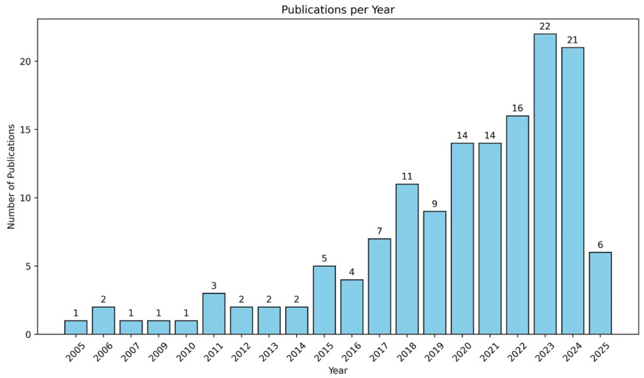

FIGURE 3 | Annual distribution of publications on vision-based and wearable sensor technologies for hand rehabilitation in stroke survivors.

3.3 | Vision-Based Technologies: Trends and Analysis

Vision-based systems, which use RGB or RGB-D cameras, constitute the dominant modality in recent publications. Unlike wearable sensors, they offer a noninvasive approach that eliminates the sensor's physical weight on the paretic limb. However, contrary to earlier claims of being fatigue-free, our analysis indicates that vision-based VR systems can induce visual fatigue and vergence–accommodation conflict (cybersickness), particularly during prolonged sessions, a factor often underreported in technical validations.

3.3.1 | *Deep Learning for Vision-Based Rehabilitation*

The field has shifted from heuristic image processing to deep learning architectures capable of modelling the complex spatio-temporal dependencies of hand movements. Recent implementations of MediaPipe have become a standard for markerless tracking on consumer hardware, extracting 33 body landmarks and 21 landmarks per hand with high fidelity [21, 22]. Beyond standard CNNs, transformer-based models are gaining traction. For instance, architectures like Swin3D [23] and SlowFast [24] significantly outperform traditional 2D CNNs in recognising egocentric rehabilitation gestures by capturing global temporal context, achieving 98.6% accuracy [18]. This trend suggests a move towards models that 'understand' the temporal evolution of therapy exercises rather than just static poses.

3.3.2 | *Virtual and Augmented Reality Integration*

Virtual reality and augmented reality serve as the primary feedback interfaces for vision-based systems. Although early systems (2010–2015) relied on simple 2D avatars, recent studies use immersive headsets (e.g., Meta Quest 2 and HoloLens 2). However, widespread adoption is hindered by cost; high-end AR headsets remain prohibitively expensive (> US\$3000) for home use compared with webcam-based solutions.

3.4 | Wearable and Sensor-Based Technologies

In our taxonomy, we categorise electromyography (EMG) and robotic assistive devices as wearable technologies, as they require physical contact with the user.

TABLE 2 | Summary of methodological quality assessment (PEDro and Downs and Black).

Study design	Count (*n*)	High quality (%)	Low/fair quality (%)
Randomised controlled trials	16	62.5%	37.5%
Quasi-experimental/ pilot studies	74	25.0%	75.0%
Case studies/ technical validations	42	N/A	N/A

Note: High quality defined as PEDro score ≥ 6/10.

3.4.1 | *Physiological and Kinematic Sensing*

Wearable systems provide more granular data than vision systems, specifically muscle activation intent via electromyography and precise joint angles via inertial measurement units (IMUs). Before visible movement occurs, EMG sensors can detect the user's intent, enabling assist-as-needed robotic control. Recent advancements have focused on fusion; for example, combining EMG with IMUs to compensate for the signal noise inherent in surface EMG sensors [25]. Crucially, not all wearables involve actuation; passive sensor gloves are increasingly used purely for kinematic tracking in home settings where the weight and complexity of a robotic exoskeleton would be impractical.

3.4.2 | *Robotic Integration*

AI-driven robotic gloves often adopt a hybrid approach. Soft robotic gloves, controlled by brain–computer interfaces (BCI) or EMG, form a closed-loop system in which the user's intent drives mechanical assistance. Combining steady-state visually evoked potentials (SSVEP) with soft robotics significantly improves functional outcomes compared to passive stretching alone [9].

4 | Technical Analysis of Vision-Based Methods

Although Section 3 outlined general trends, this section critically analyses the architectural evolution and specific technical bottlenecks (e.g., occlusion and latency) identified across the 132 reviewed studies, addressing the technical depth required for clinical deployment.

4.1 | Evolution: From CNNs to Transformers

Early systems relied on standard CNNs, which struggle with the global context required for spastic hand poses. Recent literature demonstrates a shift towards transformers. Yu et al. proposed a topology-aware transformer that explicitly models kinematic constraints, significantly outperforming CNNs in 3D pose estimation [19]. Similarly, Xu et al. introduced high-resolution pyramid vision transformer (HRPVT), which mitigates the resolution loss common in CNN downsampling, preserving fine-grained details for finger tracking [26].

4.2 | Addressing Occlusion

Hand–object interaction exercises inherently involve occlusion. Cai et al. addressed this using a hierarchical feature decoupling approach, reducing joint error during object grasping [27]. Graph convolutional networks (GCNs) are also effective; Qiu et al. used dynamic GCNs to infer occluded joint positions by exploiting geometric relationships between visible nodes [28].

4.3 | Real-Time Benchmarking for Biofeedback

For biofeedback to be effective, system latency must remain below 100 ms. Our analysis highlights FastViT [29] and MobRecon [30] as viable candidates for home-based rehabilitation, achieving mesh recovery at more than 30 fps on mobile processors. This contrasts with heavy models like Mesh-Graphormer [31], which require GPU resources unsuitable for home deployment.

5 | Hand Rehabilitation Systems

This section explores current research on hand rehabilitation, categorising methods into two modalities: computer vision and wearable devices (Figure 4). Vision-based methods use deep learning techniques to monitor and track hand movements during rehabilitation, providing real-time feedback. Wearable systems incorporate sensors directly with the patient's hand or arm and capture accurate motion data for personalised rehabilitation. We compare these approaches in terms of sensory modality, models and techniques, datasets, software frameworks, key outcomes, strengths, and limitations. This review thus provides detailed insights into how these technologies are evolving, emphasising their potential to increase the effectiveness and accessibility of hand function rehabilitation.

5.1 | Vision-Based Hand Function Rehabilitation Systems

Vision-based hand gesture recognition systems capture images and videos using cameras or depth sensors and classify hands and gestures using deep learning and other methods [32]. Unlike wearable systems, they track hand movements without sensors attached to the hand or arm, reducing calibration time and avoiding fatigue from sensor placement. These vision-based techniques are used in both hand rehabilitation robots and game systems. The general pipeline for a vision-based approach to hand rehabilitation is shown in Figure 5. The patient performs virtual exercises in front of the computer. The camera or depth sensor captures video frames, which computer vision models then process to detect hand movements and other landmarks. Based on this, the patient receives feedback to improve task performance.

5.1.1 | *Computer Vision-Based Hand Rehabilitation*

Deep learning has greatly advanced noninvasive, camera-based hand rehabilitation [33]. REST-HANDS employs egocentric smartglasses with SlowFast 3D-CNN and transformer models (Swin3D and MViTv2) for exercise recognition (98.6% accuracy) and form evaluation (86.9%) plus EfficientNetv2 for repetition counting (MAE 1.33) [18]. MediaPipe keypoint extraction (33 body, 21 finger) fused with an LSTM–CNN network achieved 95%–97.5% classification accuracy on Fugl–Meyer exercises [34]. GSFAN, a noncontact 3D model using laser-sensor hand-surface point clouds, attained 88.7% gesture accuracy [35]. A single-stage transformer network reached 92% accuracy on OUHANDS, enabling real-time adaptation [36]. Custom CNNs improved

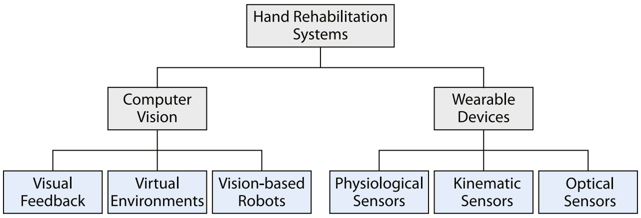

FIGURE 4 | Classification of hand rehabilitation systems, divided into two main modalities–computer vision and wearable devices–further subdivided into specific methodologies: visual feedback, virtual environments, vision-based robots and physiological, kinematic and optical sensors.

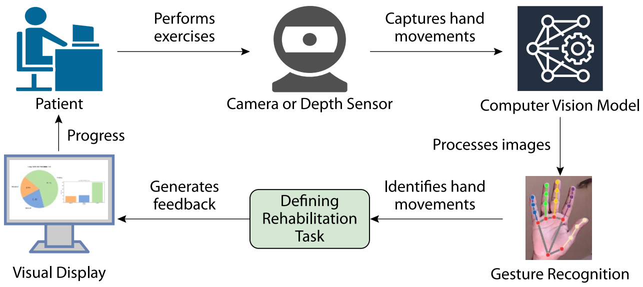

FIGURE 5 | General pipeline for vision-based hand rehabilitation. The patient performs exercises in front of a computer or a laptop. Video frames are captured using a camera or depth sensor and processed by computer vision models to recognise hand movements and landmarks. Rehabilitation tasks are defined based on this recognition, and final feedback is displayed to support improvement and monitor progress.

detection speed and accuracy by 15% [37]. Transfer-learning multiscale feature extraction has enhanced sEMG-based cross-subject recognition [38]. Parkinson's hand monitoring via deep learning has enabled personalised programmes [39]. Reviews highlight dynamic gesture techniques for game-based wrist rehabilitation [40, 41]. CNNs in the YCbCr space have improved robot assessment [42], and supervised learning for palm rehabilitation has enabled personalised therapy [43]. Privacy-preserving IoT architectures have supported vision assessments [44, 45]. Rehab-Net classifies arm movements via wearables [46], whereas mobile webcam solutions democratise access [47, 48]. 3D image–feature tracking ensures precise motion analysis [49]. Overall, integrating CNNs, transformers and 3D sensing has made vision-based hand rehabilitation more personalised, efficient and accessible. Table 3 compares key methods by dataset, models and advantages; Table 4 summarises target populations, modalities and objectives.

5.1.2 | *Virtual Environment-Based Systems for Hand Function Rehabilitation*

Integrating VR in hand rehabilitation enhances motor learning and recovery, with studies finding that video games and virtual environments reduce cognitive dysfunction more effectively than traditional methods [14, 63–68]. Recent work employs fully immersive headsets (Meta Quest 2 and HTC Vive). For example, Bressler et al. developed StableHandVR on Meta Quest 2 (Unity) using onboard optical finger tracking (no controllers) to guide repetitive exercises in a virtual farm, translating grasp, open-fist, and pronation tasks into feeding, milking and repair games. Quest tracking outperformed Leap Motion, yielding high engagement and motivation scores [69]. Other systems use desktop or semi-immersive VR. Bouatrous et al. created a Unity exergame with Leap Motion for palmar grasp exercises, adapting difficulty via k-means clustering; a pilot with 11 stroke patients showed good usability (SUS) and high intrinsic motivation [70]. Hondori et al. introduced a low-cost AR home system requiring minimal therapist involvement [71]. Wang et al.'s Leap Motion-based VR promoted motor recovery [72], and Alimanova et al. designed engaging Leap games for muscle training [73]. Yuexing et al. reviewed AI- and motion-based systems, highlighting strengths and limitations [74]. Kinect-based tracking and training were developed by Cipresso et al. [75] and Wang et al. [76]. Saini et al. proposed a low-cost home exergame framework [77], and Avola et al. presented a 3D immersive serious games system [78]. Despite lacking haptic feedback, these systems yield significant long-term improvements. Advanced VR systems include smart haptic interfaces [5], VR combined with conventional therapy [6], and telerehabilitation virtual gloves [7]. Game-based VR [2], motor imagery training [10] and preprosthetic training [12] show promise. Systems like Jintronix [8], VR mirror therapy [11] and immersive VR [79] enhance motivation and acceptance. Virtual body representations aid cerebral palsy rehabilitation [80]. Electrotactile feedback [81] and cost-effective virtual gloves [82] further improve outcomes. AR [83], mixed reality [84] and connected elbow exoskeletons [85] also support recovery. Therapy-driven gamification frameworks [86] and targeted-function systems [87–90] extend capabilities. Personalised virtual hands in neurorehabilitation [91], VR for burned-hand therapy [92] and home-based systems [93] demonstrate efficacy. Comparative trials show VR training is often as effective as conventional therapy [3, 94–97].

5.1.3 | *Vision-Based Rehabilitation Robots*

These robots are making significant strides in improving patient outcomes. A soft robotic glove controlled by an SSVEP BCI has shown superior results over traditional robotic glove therapy. By contrast, AI-driven robotic hands use EMG to detect intended finger movements [9, 98]. Brain–computer interfaces and myoelectric pattern recognition schemes enhance fine-motor skill rehabilitation, enabling real-time control of hand exoskeletons and aiding neurological recovery [99, 100]. Hybrid techniques combining hand gestures with facial expressions improve target selection for bed-bound patients, and machine-learning-based rehabilitation robots simulate workplace tasks to aid skill recovery [101–103]. Robotic systems such as the SAFER glove with sensing and force feedback, and low-cost interactive platforms, assist in motor recovery and hand therapy [104, 105], whereas vision-based-hand posture recognition systems are evolving into intelligent interfaces for robotic manipulation [106]. Cordella et al. developed a camera-based calibration system for the Gloreha Sinfonia exoskeleton glove by tracking reflective markers in closed-loop control [107]. Farulla et al. introduced a telerehabilitation system combining markerless hand tracking with a multi-joint exoskeleton for adaptive, real-time hand therapy [108]. The system demonstrated effectiveness across environments. Nam et al. designed a vision-assisted two-axis robot for upper-limb rehabilitation, enhancing stroke recovery through integrated visuo-motor feedback [109]. Table 5 compares these vision-based rehabilitation methods, including VR, AR and BCI, and their targeted patient groups.

5.2 | Wearable Devices-Based Hand Rehabilitation Systems

Gesture recognition using wearable devices involves sensors in gloves, rings, bracelets, wristbands or armbands gathering motion or physiological signal data from hand movements. This approach enables high-precision real-time recognition of various gestures and is robust to external interference. However, it can be costly, interfere with movement, lose accuracy

TABLE 3 | Comparison of vision-based hand rehabilitation systems.

System	Vision sensor(s)	Model/technique	Dataset	Framework	Key outcomes
Bae & Park (2023)—Immersive VR gesture game [50]	MetaQuest2 HMD (RGB cameras, 60 Hz)	Unity 3D + Oculus hand-tracking (22-point keypoints and threshold-based gesture recognition)	Custom (recorded finger-extension and pinch gestures)	Unity; Oculus SDK; TDK vibrotactile API	Real-time hand tracking; gesture matching success 90.0% in healthy and 79.6% in stroke subjects
Lee et al. (2024)—Vision-based soft-glove rehab [51]	RGB–D camera (e.g. Kinect)	Depth-enhanced CNN ('hand posture intention network') for hand posture classification	Custom (RGB + depth of 5 healthy and 3 stroke subjects)	PyTorch/ TensorFlow	Recognises 5 hand postures to drive an 8-DOF soft exo-glove; average accuracy 90.4% (healthy) and 80.3% (stroke)
Blais et al. (2025)—Vision-controlled exoskeleton [52]	Onboard RGB camera + Google Coral Edge TPU	MobileNet_V2 object detector; YOLOv11 tested	Custom (6 object classes for grasping)	TensorFlow Lite on Coral Edge TPU	Real-time object recognition (51 ms inference); 15.4 fps on YOLOv11; triggers pneumatic hand actuators for grasp assistance
Chen et al. (2023)—Active vision mirror therapy [21]	Monocular camera on mobile base (mecanum wheels + pan)	MediaPipe (21-point hand landmark detector) + joint-angle feature extraction + XGBoost classifier	Custom (8 gestures, 8 volunteers)	MediaPipe (Google); AutoGluon/ XGBoost	Classifies 8 rehab gestures (fist, extension, point and individual fingers) with 90% accuracy. Supports low-load mirror therapy at home (no therapist)
Zhizhong et al. (2025)—3D hand point-cloud gestures [35]	3D hand surface scanner (laser)	GSFAN (graph convolutional network on hand-surface point clouds)	Custom (hand surface point clouds, multiple subjects)	TensorFlow	Noncontact hand gesture recognition via 3D point cloud; achieved 88.7% accuracy
Luciani et al. (2025)—AR-guided arm rehab (HoloLens2) [53]	HoloLens2 (RGB camera and onboard hand-tracking)	Mixed-reality gamification (holographic trajectories/tunnels from therapist data)	Custom (therapist-recorded 3D arm paths)	Unity, MRTK (mixed reality toolkit)	Real-time kinematic feedback: Improved movement precision with holographic guides (significant vs. no feedback). Validated usability with clinicians (SUS 67.7).
Baranyi et al. (2024)—VR wrist therapy game [54]	Meta Quest (2/3) HMD (integrated hand-tracking)	Unity 3D game (escape-room puzzles) driven by detected hand gestures	N/A (game interactions)	Unity	Uses Quest's hand-tracking for gesture input; high usability in pilot; demonstrates therapist-designed VR exergame for wrist rehab
Soumis & tselikas (2025) [22]	Webcam (RGB)	MediaPipe hands (SSD palm + hand landmarks)	N/A	MediaPipe (JavaScript and TensorFlow)	Web-based serious games for hand rehab; hand tracking with a simple webcam for home use
Rana et al. (2024) [55]	Webcam (RGB)	MediaPipe hands (BlazePalm + 21 3D keypoints)	N/A	MediaPipe (Python)	Real-time tracking of hand joints; robust under variable lighting

(Continues)

TABLE 3 | (Continued)

System	Vision sensor(s)	Model/technique	Dataset	Framework	Key outcomes
Rest-HANDS (Erico et al., 2024) [18]	Egocentric smartglasses (Ray-Ban stories, RGB video)	Spatio-temporal networks (SlowFast 3D CNN, Swin3D and MViTv2)	REST-HANDS (custom egocentric hand exercises)	PyTorch (video models)	First egocentric stroke hand rehab dataset; high exercise recognition (98.6%), form evaluation (87.0%) and repetition counting (MAE 1.33)
Coox et al. (2024) [56]	VR headset (Meta Quest 2, 4 RGB cameras)	Built-in computer-vision hand tracking (Oculus hand tracking CNN)	N/A	Unity (Meta XR)	Immersive VR rehab game with pinch/grasp gestures; usability study shows effective tracking and user acceptance
Blais et al. (2025) [52]	Exoskeleton-mounted RGB camera	Custom MobileNet_V2 object detector (YOLOv11)	Custom 6-class object set	Coral Edge TPU (TensorFlow lite)	Vision-based orthotic hand exoskeleton; detects target objects to trigger pneumatic grasp (inference 51 ms); fully portable, no EMG or user calibration needed
Hu et al. (2025) [57]	Exoskeleton glove (RGB-D camera + microphone)	Vision foundation model (zero-shot segmentation for transparent objects)	N/A	Custom hierarchical control	MultiClear multimodal glove for transparent object grasping; fuses RGB-D vision and audio via a multi-layer control; 70.4% grasp success (transparent objects)
Luciani et al. (2025) [53]	HoloLens 2 (RGB + IR sensors)	Built-in HoloLens hand/arm tracking	Custom (therapist 3D trajectories)	Unity (mixed reality toolkit)	AR-guided arm rehab: Holographic tunnels and real-time feedback; significantly improved kinematic precision compared to no-feedback

when the user sweats and require calibration. Wearable devices, categorised into physiological, kinematic and optical sensors, often use multimodal data fusion for improved accuracy [25]. Figure 6 shows the general pipeline for hand rehabilitation using wearable devices. For these systems, patients wear sensors that collect hand movement data, which are transmitted to a data acquisition system and then analysed by a signal processing unit. The motion intention recognition system identifies intended movements and instructs the rehabilitation device controller to operate wearable actuators, assisting the patient's hand movements and providing feedback on progress.

5.2.1 | *Hand Rehabilitation Robots Using Physiological Sensors*

Physiological signal-driven robots decode EMG, EEG and EOG to infer motion intent. Cisnal et al. [115] used sEMG for bilateral control in RobHand; Li et al. [116] built a 16-channel sEMG exoskeleton recognising seven gestures. Soekadar et al. [117] combined EEG and EOG in a BNCI, and Zhang et al. [118] fused EEG, EOG and EMG for higher classification accuracy. Pneumatic sEMG gloves [119], ECG + EMG wearables [120] and multi-sensor platforms (IMU, ECG, EMG, GSR and SKT) [121] enhance engagement. Kim et al. [122] paired a sensing glove with a robotic glove for cooperative therapy. Elastic torque sensors [123] and closed-loop control based on angle and pressure sensors [124] refine assistance. These systems show promise but require improvements in comfort, robustness and safety for unsupervised use.

5.2.2 | *Hand Rehabilitation Robots Using Kinematic Sensors*

Kinematic-sensor robots use angle, accelerometer, gyroscope and pressure data for precise motion tracking. Yap et al. [125] designed an MRC glove with angle sensors; Rahman et al. [126] designed a bilateral-angle exoskeleton. Nilsson et al. [127] created SEM gloves with pressure feedback. Chen et al. [128] combined soft sensory and motor gloves with ML gesture recognition for stroke paralysis. Rakhtala [124] integrated angle and pressure sensors for adaptive closed-loop control. These high-precision systems suit detailed, late-stage rehabilitation.

TABLE 4 | Selected studies using vision-based technologies for hand rehabilitation.

Author (year)	Population	Dataset	Raw data	Feature	Objective
Chen et al. (2023) [21]	Stroke survivors (hand hemiparesis)	$N = 18$ healthy (gesture dataset)	Monocular RGB video	Hand keypoints (8 gestures)	Vision-based mirror therapy with gesture control
Tahsin et al. (2024) [58]	Stroke patients (upper-limb)	TRSP dataset (19 subjects: 9 stroke and 10 healthy)	Xbox Kinect RGB-D (3D skeletal data)	3D joint coordinates/angles (shoulder, elbow)	Classify rehab stage (compensatory movements)
Simonsen et al. (2017) [59]	Subacute stroke (arm paresis)	$N = 11$ stroke patients (feedback vs. control)	Kinect depth (hand tracking)	2D hand position (marker in target)	Adaptive visual feedback to improve movement smoothness
Simonsen et al. (2016) [60]	Stroke (hemiparetic hand)	Pilot study	Kinect depth + object tracking	Grasp detection (cylindrical objects)	Closed-loop FES for grasp assistance
Simonsen et al. (2017) [59]	Chronic stroke (hand deficits)	$N = 11$ stroke patients	Kinect RGB-D	Task timing (automated Jebsen test)	Automate hand dexterity assessment (Jebsen test)
Du et al. (2022) [61]	Stroke patients (hand dysfunction)	$N = 82$ stroke patients	RGB video + optical motion capture	Wrist/finger joint angles and kinematics	Vision-based quantitative hand assessment (MDIVQAS)
Ham et al. (2024) [62]	Hemiplegic stroke (finger dysfunction)	$N = 21$ hemiplegic stroke patients	Mixed-reality setup (depth camera + palm camera)	Finger flexion/ extension tracking	Mixed-reality hand/finger rehab (interactive games)
Ain et al. (2021) [63]	Chronic stroke (upper-limb paresis)	$N = 56$ chronic stroke (28 Kinect VR + 28 control)	Kinect (RGB-D)	Upper-limb movement (FMA-UE components)	Kinect-based VR training to improve arm/hand function

5.2.3 | *Hand Rehabilitation Robots Using Optical Sensors*

Optical-sensor robots utilise fibre or photoelectric sensing for fine force and posture measurement. He et al. [129] introduced an optical fibre pressure sensor for real-time force feedback; He et al. [130] added photoelectric posture sensing. Diez et al. [131] embedded micro-optical force sensors in a lightweight exoskeleton, and Liu et al. [132] used fibre curvature sensors in a soft actuator. These designs offer high sensitivity and compactness, though cost and calibration remain challenges. Table 6 summarises the key outcomes for soft robotic glove systems.

6 | Hand Rehabilitation Applications and Technologies

6.1 | Applications

Hand rehabilitation employs vision-based, virtual environment, serious gaming and robotic systems to restore function after stroke or injury [149].

6.1.1 | *Vision-Based Hand Function Rehabilitation Systems*

Noninvasive camera systems track hand kinematics and deliver real-time feedback to assess function and guide exercises [9, 101, 150–152]. Applications include gesture recognition, quantitative hand assessment and adaptive training programs [98].

6.1.2 | *Virtual Environment-Based Systems*

6.1.2.1 | *VR and AR Systems.* Immersive 3D environments (Oculus Rift [153], HTC Vive [154]) gamify exercises to enhance motivation, motor learning and remote monitoring, proving effective in stroke recovery, motor imagery and prosthetic training [2, 3, 5, 6, 8, 10–12, 79–97, 155]. AR systems overlay holographic cues (HoloLens [156]) onto real-world environments to personalise therapy and improve engagement [2, 83, 86].

6.1.3 | *Serious Games*

Serious game-based rehabilitation transforms exercises into goal-driven tasks with instant feedback and rewards, boosting adherence and outcomes [3, 67, 86, 87].

6.1.4 | *Computer Vision-Based Hand Rehabilitation Robots*

6.1.4.1 | *AI and Robotics.* AI-based EMG and vision-controlled robots (soft gloves, BCI systems) deliver adaptive assistance. Examples include myoelectric exoskeletons [99, 100], SSVEP-controlled soft gloves [9, 98], and intelligent robotic interfaces [102, 104–106, 157–160].

6.1.4.2 | *Benefits.* These systems improve fine motor skills, enhance neurocognitive engagement and personalise therapy through real-time feedback and data-driven adaptation [9, 98].

6.2 | Technologies

Virtual rehabilitation employs vision-driven techniques, immersive environments and sensor-based tracking to assist patients and provide tailored feedback.

TABLE 5 | Comparison of VR, AR and robotic hand rehabilitation systems for stroke.

Author (year)	Vision sensor(s)	Model/technique	Dataset	Framework	Key outcomes
Cha et al. (2021) [110]	Dual RGB cameras	Upper-limb motion capture (arms and fingers) in VR (avatar control)	Pilot trial, 27 patients	Custom VR environment	Improved embodiment (body ownership and agency) and significantly larger Fugl–Meyer gains versus control.
Wang et al. (2017) [72]	Leap Motion controller	VR exergames for hand motions	RCT, 26 patients	PC-based VR software	Significant improvement in Wolf Motor Function Test and contralateral sensorimotor activation for VR versus control.
Kim et al. (2018) [111]	Microsoft Kinect (depth)	VR rehabilitation games	RCT, 23 patients	Custom Kinect VR system	VR group had higher arm activity counts than sham but no significant difference in Fugl–Meyer score.
Shin et al. (2022) [112]	RAPAEL smart glove (IMU + bend)	Soft glove with game-based VR	RCT, subacute stroke	Proprietary VR platform	Glove + VR group showed greater upper-extremity motor gains (FMA, Jebsen–Taylor) and increased cortical activation versus conventional therapy.
Gao et al. (2023) [113]	EEG (MI-based BCI) + soft robotic glove	Motor-imagery BCI with VR feedback	Small trial, $n = 11$	Custom BCI + VR + glove system	Enhanced cortical engagement and improved muscle strength, tone and hand function.
Luciani et al. (2025) [53]	HoloLens 2 (IR/RGB-D, IMUs)	AR real-time kinematic feedback (holographic trajectories)	15 healthy subjects	Unity + MRTK	Improved movement accuracy with feedback, usability (SUS = 67.7) and acceptance (TAM = 4.4/5).
Li et al. (2024) [114]	Force-feedback hand exoskeleton	Robot-assisted task-oriented training	RCT, 44 patients	Robotic control software	Experimental group showed greater FMA-hand, ARAT, grip strength and ROM gains versus control after 4 weeks.

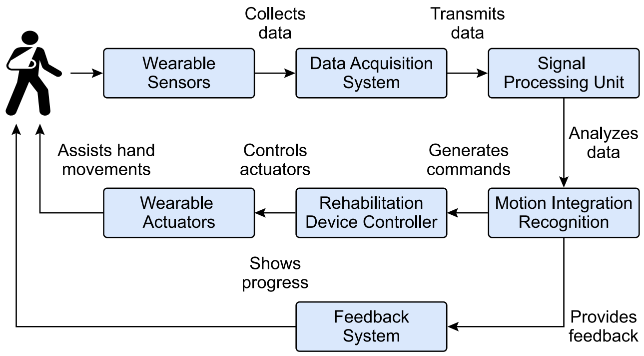

FIGURE 6 | General pipeline for hand rehabilitation using wearable devices. Sensors collect hand movement data, transmit it to a data acquisition system and analyse it. Motion intention recognition identifies intended movements, commands the device controller and operates wearable actuators. Feedback is provided to help the patient improve and to monitor progress.

6.2.1 | *Advanced Techniques*

In virtual environments, motion tracking and sensors record precise hand kinematics. Muscle and joint activity is recorded using EMGs, IMUs and pressure sensors, enabling accurate exercise control and evaluation.

6.2.2 | *Use of Sensors and Motion Tracking*

Wearable and camera-based sensors produce real-time digital representations of hand movements. Adaptive exercise protocols are made possible by force sensors measuring interaction, IMU tracking orientation and EMG measuring muscle activation.

6.2.3 | *Immersive Technologies (VR/AR)*

VR immersion (e.g., HTC Vive [154] and Oculus Rift [153]) immerses users in simulated tasks, thereby improving motor learning and motivation. With real-time visual and aural feedback, AR headsets like HoloLens [156] support home-based therapy [5, 6].

7 | Discussion and Future Directions

7.1 | The Data Reproducibility Gap

A critical barrier is the reliance on custom datasets. Although benchmarks like FreiHAND [161] and DexYCB [162] exist, fewer than 15% of clinical studies use them. Instead, validation often occurs on small, private cohorts ($n < 20$), leading to accuracy metrics that do not generalise to stroke survivors.

TABLE 6 | Comparison of soft glove-based rehabilitation systems.

Reference	Device	Technique	Dataset	Platform	Key outcomes
Chen et al. (2021) [133]	SExoG glove	sEMG-driven bilateral mirror training; 2-step NN + state exclusion model	4 stroke (70/30 split)	OpenBCI, Keras NN	Mean gesture accuracy 98.7%, enabling mirrored control of nonparetic hand
Guo et al. (2018) [134]	Soft exo-sheath	sEMG + SVM intent detection; DC motor, Bowden cable	In-lab (no dataset)	RFD77101 μC	Reliable EMG; fast/accurate low-level control; safe assistance
Shi et al. (2021) [135]	Soft robotic glove	EMG-driven pneumatic flex/ext	16 stroke (20 sessions)	Not specified	Gains: ARAT+2.44, FMA+3.31 and BBT+1.81; mild spasticity subgroup
Sun et al. (2023) [136]	Assistive glove	Myo EMG + NN + force estimation	9 stroke (online tests)	Thalmic myo, custom NN	Hybrid BCI control effective in assisting grasp; functionally validated
Lim et al. (2023) [137]	Pneumatic glove	Pneumatic actuators for ADL tasks	8 stroke (grasp tasks)	Pneumatic control box	Significant improvement in ADL object manipulation and confidence
Thimabut et al. (2022) [138]	Cable-driven glove	Pneumatic cables for assisted grasp	20 stroke (ARAT, BBT)	Glove with hoist/cable	Box + Block +6.4, ARAT +27.1%, grip +28.8%; effective in severe cases
Zhang et al. (2024) [103]	Robotic glove	MI + SSVEP BCI: FBCCA + FBCSP + CNN	12 healthy + 9 stroke	EEG, Unity VR	Accuracy: 95.8% (healthy) and 63.3% (stroke); feasible BCI control
Yurkewich et al. (2020) [139]	My-HERO glove	EMG (3-channel) for grasp/release intent	9 stroke (grasp)	Onboard controller	FMA-hand +8.4, CAHAI +8.2; intent accuracy 84.7%; high satisfaction
Barria et al. (2023) [140]	RobHand exoskeleton	Passive flex/ext; motors + Windows GUI	4 stroke (16 sessions)	LabVIEW, motors	Safe, tolerable; high satisfaction, but no significant hand function gains
Yap et al. (2017) [141]	Pneumatic glove	Pneumatic flexion; soft actuators	2 stroke (pilot)	Pumps + actuators	Functional grasp w/o effort; high comfort and transparency
Rieger et al. (2023) [142]	Pneumatic glove	Steel-resistive flex/ext actuators	10 healthy	Arduino, Unity	Flexion 81%; supports stroke use; 18% tip force loss with steel
Zondervan et al. (2016) [143]	MusicGlove	Sensor game; grasp triggers music	17 stroke (RCT)	Game software, Bluetooth	MAL +0.36 quality, +0.35 amount; intensive home use feasible
Zare et al. (2025) [144]	NeuroFlex glove	EEG MI decoder (transformer CNN)	10 healthy	EEG, custom CNN	High EEG-MI control performance; robust online metrics
Abbate et al. (2023) [145]	VR mirror + glove	Mirror VR + soft glove exo	21 healthy (usability)	Oculus VR	High usability, no sickness; viable mirrored motion feedback
Casas et al. (2021) [146]	HandSOME II	Passive spring extension	10 stroke (8-week home)	Magnetometer sensors	Gains: ARAT +3.4, MAS −0.21 and MAL +0.58; retained at 3 months
Kang et al. (2020) [147]	RAPAEL glove	Bend + IMU sensors; adaptive AI games	30 stroke (RCT)	PC/tablet software	FMA-UE ↑ ($p = 0.023$); better BBT, coordination and feasibility shown
Shi et al. (2024) [148]	EMG robotic hand	Personalised EMG pattern recognition	34 stroke (RCT)	EMG armband	HT group > robot: FMA, ARAT, BBT and AROM improved ($p < 0.05$)

(Continues)

TABLE 6 | (Continued)

Reference	Device	Technique	Dataset	Platform	Key outcomes
Chen et al. (2020) [128]	Mirror SExoG	Mirror therapy + sEMG + ML	4 stroke	Custom glove, ML models	Offline gesture accuracy 99.4%, real-time 82.2%; validated bilat. training
Chen et al. (2021) [128]	Mirror glove + vision	Vision gesture + actuated mirror therapy	Healthy (PoC)	Wearable + camera	Independent mirrored training; no glove on healthy hand needed

TABLE 7 | Comparative framework: Vision versus wearable modalities.

Feature	Vision-based systems	Wearable systems
Primary sensor	RGB/RGB-D cameras (remote)	IMU, sEMG, and soft sensors (on-body)
Setup time	Low (zero-setup feasible)	High (donning/doffing required)
Precision	Moderate (e.g., ~1.5–2.5 cm MAE)	High (e.g., ~2–5° joint-angle RMSE)
Fatigue factor	Visual fatigue and cybersickness	Physical fatigue (weight)
Cost profile	Low (consumer webcam/smartphone)	Moderate to high (custom hardware)

Note: Quantitative ranges for precision and error are indicative approximations synthesised from the technical validation studies reviewed in Sections 3 and 4 (e.g. [21, 129]), representing typical mean absolute error (MAE) or root mean square error (RMSE) reported. Cost profiles compare consumer hardware with clinical-grade robotic systems.

7.2 | Cost and Latency Thresholds

To transition from research prototypes to viable home-rehabilitation tools, systems should meet specific quantitative guidelines. Financially, our analysis suggests that home-based systems should aim for an indicative affordability target of approximately US$500. This target is supported by the feasibility of recent successful trials using consumer-grade hardware, such as the Meta Quest 2 headset (Bressler et al. [69]) and standard webcams (Soumis and Tselikas [22]), which offer scalable alternatives to clinical robotic systems, which cost over US $15,000.

Technically, for visual biofeedback to be effective, it is generally recommended that end-to-end (motion-to-photon) system latency remain below approximately 100 ms. This design guideline, established in the VR and HCI literature [153], helps preserve the user's sense of agency and minimises the risk of cybersickness. Recent edge-optimised architectures demonstrate the feasibility of meeting these perceptual guidelines on consumer hardware [29, 30]. To synthesise these findings, Table 7 presents a comparative framework evaluating the trade-offs between vision-based and wearable modalities across these key clinical and technical dimensions.

7.3 | Future Research Directions

Technology for hand rehabilitation has advanced significantly, but significant issues still need to be resolved. The efficacy and personalisation of vision-based systems are often limited by their inability to modify exercise difficulty or feedback in real time based on patient performance. The integration of markerless tracking into established therapeutic protocols remains a persistent challenge [8], and advanced sensors like HoloLens 2 are too expensive for widespread clinical use [53]. Future research should focus on developing adaptive AI models, such as reinforcement learning frameworks, that adapt therapy to individual progress dynamically [10]; developing affordable, mobile and webcam-based vision solutions to improve accessibility [22]; and combining virtual and traditional rehabilitation modalities to create hybrid interventions that leverage the benefits of both approaches [110].

Wearable systems also face issues: High-precision exoskeletons like RobHand often compromise user comfort [140], whereas devices incorporating EEG raise data privacy and security concerns [144]. Additionally, many EMG-driven robotic gloves lack comprehensive, long-term clinical validation [34]. Addressing these problems will require designing more ergonomic soft robotic gloves [142], using federated learning techniques to protect sensitive physiological data [120] and running large-scale, long-term clinical trials to determine the safety and effectiveness of wearable systems [138].

Critical requirements beyond modality-specific advancements include expanding immersive augmented and mixed reality environments to improve patient engagement [53], integrating multimodal feedback channels, such as haptic, visual and auditory cues, to reinforce motor learning [81], using artificial intelligence for the dynamic personalisation of therapy protocols [91], and encouraging the creation of standardised clinical guidelines to ensure interoperability and facilitate widespread adoption.

8 | Conclusions

This systematic review analysed 132 studies to critically evaluate the state of vision-based and wearable technologies for post-stroke hand rehabilitation. The field is characterised by rapid innovation in deep learning architectures but suffers from a lack of standardised benchmarking and large-scale clinical validation. Our analysis indicates that although vision-based systems using modern architectures like transformers offer a compelling, low-cost solution for home therapy, they must adhere to strict latency constraints (< 100 ms) to be clinically effective. For stroke survivors, these AI-integrated technologies enable unsupervised practice at home, which substantially increases therapeutic intensity, a critical factor in supporting neuroplasticity. Future research must prioritise the creation of public, stroke-specific datasets and the development of privacy-preserving, edge-computing models to bridge the gap between engineering novelty and clinical reality.

Author Contributions

Kamal: conceptualization, formal analysis, methodology, writing – original draft. **Debanga Raj Neog:** data curation, investigation, supervision, validation, writing – review and editing. **M. K. Bhuyan:** funding acquisition, project administration, supervision, writing – review and editing. **Karl F. MacDorman:** validation, writing – review and editing. **Ram Kumar Karsh:** resources, visualization. **Rabul Hussain Laskar:** formal analysis.

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The authors declare no conflicts of interest.

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