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Research Article

ARTIFICIAL INTELLIGENCE IN COMMUNITY BASED REHABILITATION: A SYSTEMATIC REVIEW

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ABSTRACT:
Background: Community-Based Rehabilitation (CBR) is a strategy to promote inclusion, independence, and participation for people with disabilities, particularly in low-resource settings. In recent years, artificial intelligence (AI) has been increasingly used in clinical rehabilitation; however, its integration into community contexts remains limited. **Objective:** This systematic review aimed to identify and synthesize recent evidence on the use of AI technologies within CBR. **Methods:** A systematic search was conducted in PubMed, Scopus, and ScienceDirect for articles published from January 2020 to July 2025. Eligible studies included empirical research applying AI in CBR contexts. Two reviewers independently screened, extracted data, and assessed risk of bias using RoB2, ROBINS-I, PROBAST, and QUADAS-2. **Results:** From 842 identified records, 10 studies met inclusion criteria. Applications of AI in CBR were grouped into prediction and screening, home-based or remote rehabilitation, patient empowerment, and social support. Reported benefits included improved cognition, sarcopenia reversal, frailty and depression screening, diabetes self-management, and smoking cessation. Socially assistive robots were found acceptable and useful in supporting daily activities and emotional well-being. Limitations across studies included small samples, short follow-up, limited external validation, and a focus on technologically literate populations. **Conclusion:** AI shows considerable potential to strengthen the accessibility, personalization, and effectiveness of CBR. Future research should focus on large-scale, long-term studies with diverse populations and explore strategies for equitable, sustainable integration of AI into community rehabilitation services.

Keywords: Artificial intelligence, community-based rehabilitation, machine learning, digital health, frailty, assistive technology

1 | INTRODUCTION

Community-Based Rehabilitation (CBR) is a multifaceted strategy introduced by the World Health Organization (WHO) to promote the inclusion and participation of people with disabilities within their own communities, particularly in resource-limited settings. It emphasizes a rights-based approach, mobilizing local resources to improve access to health, education, livelihood, and social integration. Over time, CBR has evolved into a comprehensive framework that addresses the diverse and long-term needs of individuals with disabilities across the life course.[1] Globally, more than 1.3 billion people—approximately 16% of the world's population—live with some form of disability.[2] This number is projected to rise due to population aging, higher incidence of chronic diseases, and improved survival following illness or injury. The WHO Rehabilitation 2030 initiative estimates that at least 2.4 billion people worldwide require rehabilitation services, representing more than one in every three individuals.[3,4] However, in many low- and middle-income countries (LMICs), over half of these individuals do not receive adequate services because of workforce shortages, insufficient infrastructure, and inequitable distribution of care.[3,4] These challenges are particularly pronounced in community settings, where limited access to specialized care is compounded by geographic isolation, financial constraints, and shortages of healthcare personnel. Innovative solutions are urgently needed to bridge service delivery gaps and to enhance the quality and accessibility of CBR programs. The integration of artificial intelligence (AI), including machine learning and deep learning, offers transformative opportunities for community-based health services. AI has been successfully applied in multiple fields of clinical medicine, such as diagnostics, prognostics, and remote patient monitoring.[5]

In rehabilitation, AI has been increasingly used to develop adaptive rehabilitation platforms, intelligent assistive devices, predictive models for functional recovery, seamless data integration, real-time monitoring, and remote consultations—ultimately improving adherence and care coordination. Emerging technologies such as AI, the metaverse, and advanced data science further personalize treatment, create immersive therapy environments, and strengthen clinical decision-making through large-scale data analysis.[6] Despite these advances, most applications remain concentrated in institutional or hospital-based contexts, with limited translation into community-based rehabilitation.[6] To date, no comprehensive synthesis has examined how AI has been applied within the framework of CBR. A better understanding of the current landscape of AI applications in this area is crucial for guiding innovation, investment, and policy development. This systematic review offers an important advancement by presenting one of the earliest focused examinations of how artificial intelligence (AI) is incorporated into community-based rehabilitation (CBR). By categorizing existing evidence into four key areas—AI for prediction and screening, home-based or remote rehabilitation, behaviour modification and patient empowerment, and social support—the study provides a structured perspective on the breadth of AI applications in community contexts. The findings demonstrate that AI-enabled interventions are generally feasible, acceptable, and show promising early outcomes, including gains in cognitive functioning, physical performance, frailty identification, depression risk detection, and user engagement. At the same time, the review draws attention to common methodological challenges such as small study samples, limited external validation, short follow-up periods, and restricted participant diversity, highlighting the need for more robust and inclusive research designs. By synthesizing these insights, the study helps guide future research priorities and supports policymakers and practitioners in developing equitable, scalable, and sustainable strategies for integrating AI into CBR services. Drawing from the background outlined above, this review aims to address the following question: In what ways are artificial intelligence tools being utilized within community-based rehabilitation, and what current evidence describes their effectiveness, practicality, and challenges in the areas of home-based rehabilitation, risk prediction and screening, patient empowerment, and social support?"

2 | MATERIAL AND METHODS

2.1 | Study Design and Protocol

This systematic review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines. The purpose of this review was to identify, evaluate, and synthesize studies that reported the application of artificial intelligence (AI) technologies in community-based rehabilitation.

2.2 | Data Sources

A comprehensive literature search was conducted in PubMed, Scopus, and ScienceDirect, covering publications from January 2020 until 1 August 2025. To ensure sensitivity, various keyword combinations were applied using Boolean operators. These included "artificial intelligence," "machine learning," "deep learning," "intelligent system*," "predictive model*," and "algorithm*" combined with "community based rehabilitation," "community dwelling," "community rehabilitation," or "home based rehabilitation." Broader combinations were initially explored to minimize the risk of missing relevant studies. The five-year timeframe was chosen to capture recent evidence and to provide an updated synthesis that complements earlier reviews focusing on older studies.

2.3 | Selection Strategy

Studies were considered eligible if they were original empirical research, published in English, and available in full text between 2020 and 2025. Eligible designs included randomized controlled trials, non-randomized studies, and observational studies. The target populations were individuals or groups engaged in community-based rehabilitation services, and the interventions involved the application of AI technologies, including machine learning, predictive models, deep learning, natural language processing, and intelligent assistive technologies. Studies were excluded if they were non-original works such as reviews, editorials, letters, conference abstracts, or if they examined AI exclusively in hospital or clinical settings without a community component

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2.4 | Study Selection

Three reviewers independently screened titles, abstracts, and full texts in a three-stage process. At each stage, irrelevant studies were excluded according to the predetermined eligibility criteria. Discrepancies between reviewers were resolved through discussion, and a fourth reviewer was consulted if necessary. After thorough evaluation, the final list of included studies was established by consensus.

2.5 | Data Extraction and Quality Assessment

Data extraction was performed using a structured form developed in Microsoft Excel, which was pilot-tested on a subset of studies to ensure consistency and relevance. Two reviewers independently extracted data on study identification, design, sample size, setting, population characteristics, AI methods and functions, CBR domains, measured outcomes, main findings, and reported limitations. Any disagreements were resolved by discussion or, if required, by consulting a third reviewer. The methodological quality and risk of bias of included studies were assessed using validated tools appropriate for each design. Randomized controlled trials were appraised with the Cochrane Risk of Bias 2 (RoB2) tool, non-randomized studies with the Risk of Bias in Non-Randomized Studies of Interventions (ROBINS-I), diagnostic accuracy studies with QUADAS-2, and prediction model studies with the Prediction model Risk of Bias Assessment Tool (PROBAST). Each domain was rated as low, moderate, or high risk of bias, or "unclear" if insufficient information was available. Assessments were conducted independently by two reviewers, and disagreements were resolved by consensus or by adjudication from a third reviewer. The risk of bias assessments were incorporated into the interpretation of evidence strength but were not used as exclusion criteria.

3 | RESULTS

3.1 | Selection

The systematic search yielded a total of 842 records from PubMed, Scopus, and ScienceDirect. Following the removal of 30 duplicates and 250 records marked as ineligible by automated tools, 810 unique articles were screened by title and abstract. Of these, 787 were excluded for not meeting inclusion criteria, leaving 23 articles for full-text review. After a careful assessment, two reports could not be retrieved, and another 21 were evaluated for eligibility. Sixteen articles were subsequently excluded for the following primary reasons: the absence of rehabilitation, empowerment, or community-based intervention; non-AI or non-ML technologies; insufficient sample size or feasibility-only designs; studies not based in a community setting or targeting populations outside of interest; or other reasons, such as not implementing or evaluating an AI intervention. Ultimately, five studies met all criteria and were included in the final qualitative synthesis. The study selection process is detailed in Figure 1.

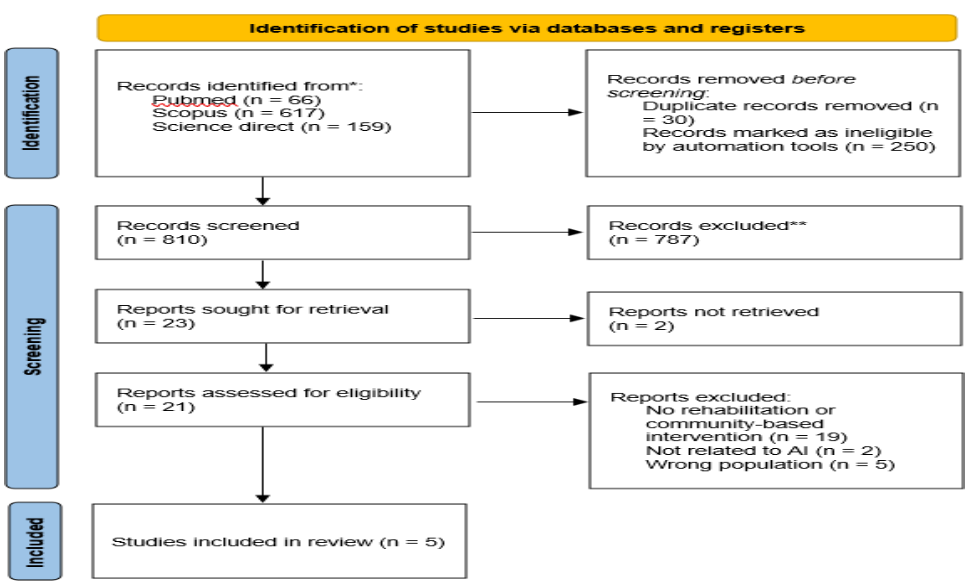

Figure 1 PRISMA flow diagram of study screening and selection

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3.2 | Quality Assessment

The included studies represent a wide range of research designs and applications of artificial intelligence (AI) and machine learning (ML) in health and aging. Study designs encompassed randomized controlled trials (RCTs) (including double-blind, protocol, and cluster-randomized designs), non-randomized experiments, observational and mixed-methods studies, as well as model development and diagnostic accuracy studies. Each was assessed for risk of bias using standardized tools suitable for their design, including RoB 2 for RCTs (Figure 2), ROBINS-I for non-randomized and observational studies (Figure 3), PROBAST for predictive modeling (Figure 4), and QUADAS-2 for diagnostic studies (Figure 5). AI was applied to interventions such as cognitive training, exercise sequencing, automated motivational messaging, social robot support, rehabilitation monitoring, technological implementation in clinical settings, and health prediction or diagnosis using ML algorithms and voice biomarkers. Overall, most studies were rated as having a moderate risk of bias, with only two studies one double- blind RCT evaluating computerized cognitive training and one RCT protocol assessing ML- based SMS motivation—receiving low risk of bias ratings. Moderate risk was most attributed to limitations in methodology, such as incomplete blinding, small sample sizes, potential confounding, or insufficient external validation of predictive models. These findings underline the diversity of AI approaches in current aging research, as well as the prevailing need for improved study design and transparent reporting to reduce the risk of bias in future investigations.

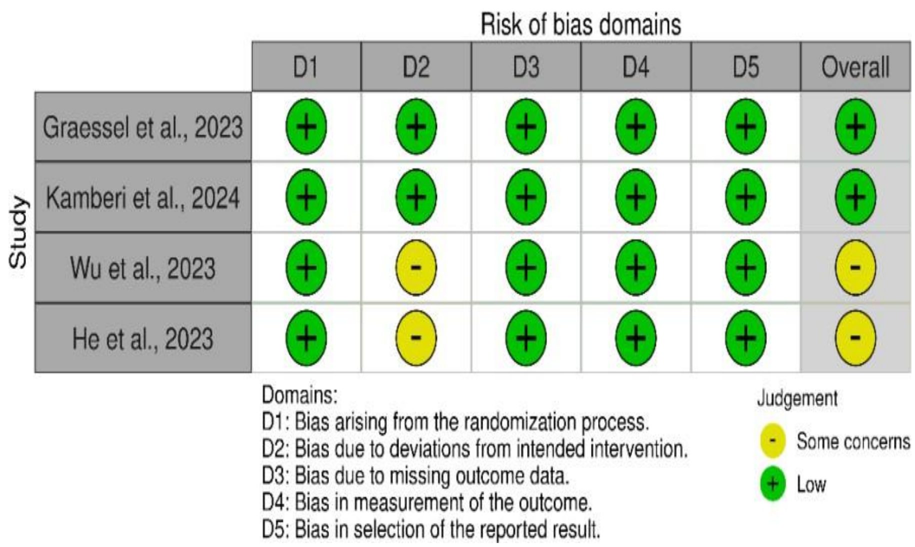

Figure 2 Risk of Bias assessments using RoB2

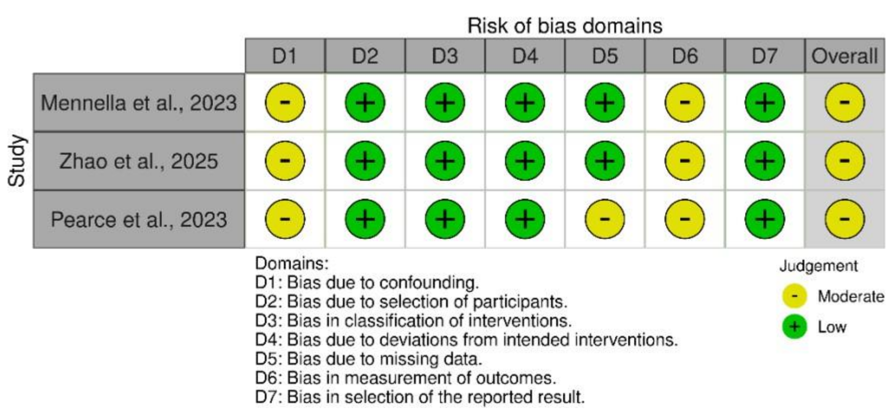

Figure 3 Risk of bias assessment using ROBINS-I

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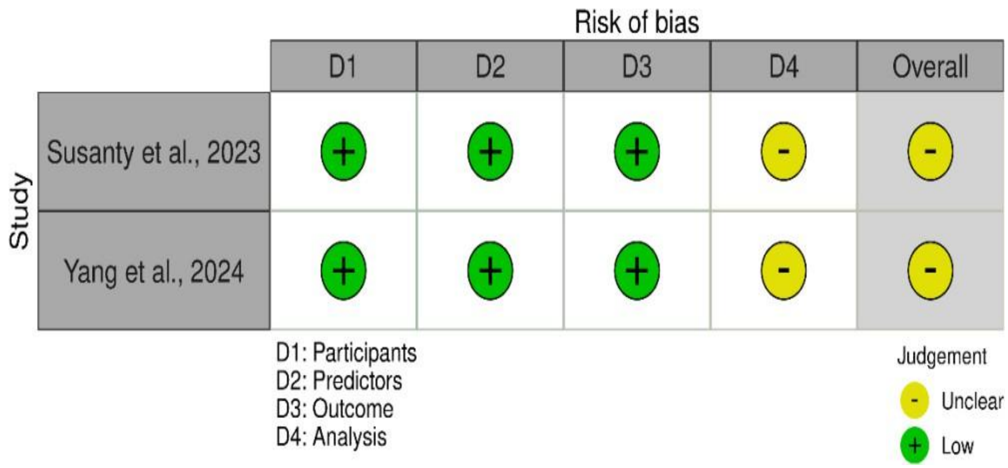

Figure 4 Risk of bias assessments using PROBAST

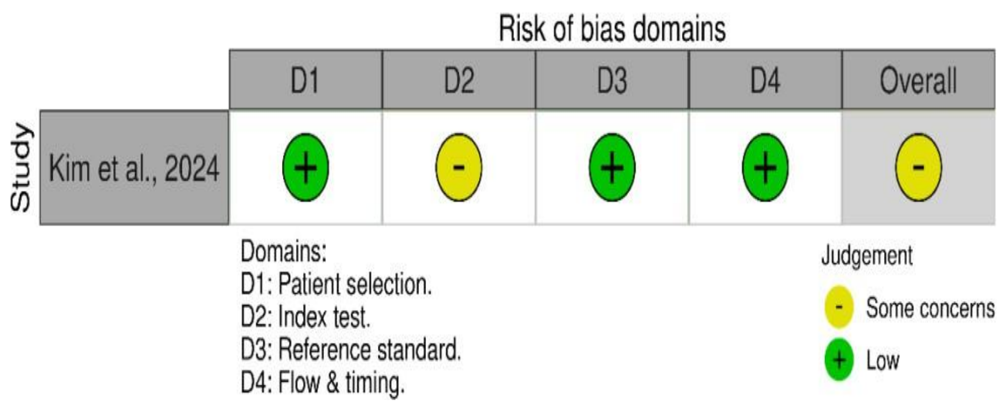

Figure 5 Risk of bias assessment using QUADAS

A total of ten studies were included in this review, examining the application of artificial intelligence (AI) technologies within the context of community-based rehabilitation (CBR). These studies varied in terms of methodology, population demographics, AI approaches, and rehabilitation goals. To enhance clarity and comparability, the findings have been put in order based on the primary AI functionality employed in each study. The five identified functional categories are: (1) prediction and screening, (2) home-based or remote rehabilitation via ai, (3) behaviour changes or patient empowerment, and (4) social support. Grouping the studies in this manner provides a structured perspective on how AI technologies are being integrated into various CBR domains—such as health, empowerment, social support, and functional recovery—and highlights the diverse range of AI tools (e.g., deep learning, explainable AI, Bayesian networks) currently being explored. A detailed summary of each study, including AI technology used, targeted CBR domains, outcome measures, and main findings, is presented in Table 1.

3.3 | Home-based or Remote Rehabilitation via AI

These past few years back have shown an amazingly rapid advancements in the application of artificial intelligence (AI) across community-based and home rehabilitation, with studies[7,8,9] such illustrating varied approaches to leveraging AI for improved care delivery. These interventions span adaptive, individualized cognitive training[8],remote monitoring of physical rehabilitation exercises using deep learning[7] integration and clinician adoption of advanced technologies such as robotics, virtual reality, and sensors in routine rehabilitation practice [9] and the tailoring of exercise sequences through explainable AI for sarcopenia management [10] Collectively, these studies highlight the growing trend toward deploying AI-enabled technologies directly within patients' homes or community environments. By increasing accessibility, optimizing therapy regimens, and enhancing both adherence and outcomes, AI offers the means to extend high- quality rehabilitation beyond traditional healthcare facilities.

A double-blind randomized controlled trial assessed the effect of individually adaptive, machine learning–driven computerized cognitive training (iCCT) versus basic computerized cognitive training (bCCT) in community-dwelling adults aged 60+ with mild cognitive impairment (MCI). The study enrolled 89 participants (mean age 73.5, 41.6% female, highly educated) living independently in Germany. Participants completed 6 months of home-based training; adherence was high (average 3–4 sessions/week, 35 minutes/session). The primary outcome, change in Montreal Cognitive Assessment (MoCA) score, improved more in the iCCT group (+2.2) versus bCCT (+0.9; p=0.029). Additionally, 51% of the iCCT group reversed out of MCI status compared to 29% in bCCT (p=0.033). User experience was rated higher for iCCT. No long-term follow-up outcomes were collected.

Study ID	Title	Study Design & Methodology	Population Characteristics	AI Technology Details	CBR Matrix Domain	Outcomes Measured	Main Findings	Limitations
Graessel et al., 2023, Germany	Individualised Computerised Cognitive Training (iCCT) for Community-Dwelling People With Mild Cognitive Impairment (MCI): Results on Cognition in the 6-Month Intervention Period of a Randomised Controlled Trial (MCI-CCT Study)	Double-blind RCT; n=89; 6-month virtual intervention; iCCT vs active control (bCCT)	Community-dwelling adults aged 60+ with psychometric MCI; n =89; Germany	Function: individualized cognitive training; Type: machine learning; Platform: virtual home-based CCT	Health, Social Participation	MoCA score change; usage frequency; user satisfaction	iCCT significantly improved cognition compared to bCCT; ML enhanced engagement and effectiveness; average 3 sessions/week, 35 mins/session	Small sample size; short duration; limited generalizability; self-reported adherence
Mennella et al., 2023, Italy	A Deep Learning System to Monitor and Assess Rehabilitation Exercises in Home-Based Remote and Unsupervised Conditions	Experimental study using custom dataset of 6 resistance training exercises; real-time ROM and compensatory movement analysis	One rehabilitation expert performing correct and incorrect versions of six resistance training exercises	Function: motion assessment; Type: deep learning; Platform: real-time home-based system	Health	Accuracy of ROM and compensatory movement detection	System demonstrated 89% ROM classification accuracy and 98% compensatory movement detection accuracy; strong potential for home rehab support	No patient sample; not tested in real-world clinical settings
Pearce et al., 2023, Australia	Advanced Technology in a Real-World Rehabilitation Setting: Longitudinal Observational Study on Clinician Adoption and Implementation	Longitudinal observational study over 12 months in clinical rehab setting	Allied health clinicians (n=119) and patients (n=269) with stroke, SCI, or brain injury; inpatient, outpatient, and community rehab	Function: therapy delivery and monitoring; Type: robotics, VR, sensors, FES; Platform: clinical setting	Health, Empowerment	Tech use frequency; device types; clinician involvement; therapy dosage	Technology use varied by setting and diagnosis; outpatient settings showed highest adoption; training and tailored strategies critical for uptake	Observational design; no direct patient outcomes; limited to one provider

Study ID	Title	Study Design & Methodology	Population Characteristics	AI Technology Details	CBR Matrix Domain	Outcomes Measured	Main Findings	Limitations
He et al., 2023	Self-determined Sequence Exercise Program for Elderly With Sarcopenia: A Randomized Controlled Trial With Clinical Assistance From Explainable Artificial Intelligence	Double-blind RCT; n=94; 24-week intervention (control, STG, SDSG); ML model used for sarcopenia prediction and explanation	Community-dwelling older adults aged 60–75 with sarcopenia (AWGS criteria); n=94	Function: sarcopenia reversal prediction; Type: explainable ML stacking model; Platform: offline model with SHAP interpretation	Physical Rehabilitation / Functional Recovery	Sarcopenia reversal; SMFD; SMFA; SMD; SMA; RSMI; grip strength; model accuracy	SDSG group showed greatest improvement in strength and muscle metrics; 47% reversal rate in SDSG; ML model effectively predicted outcomes	Limited sample; no external model validation; short intervention; self-reported adherence
Susanty et al., 2023, Indonesia/Taiwan	Questionnaire-Free Machine-Learning Method to Predict Depressive Symptoms Among Community-Dwelling Older Adults	Development and validation of ML models (logistic regression, random forest, gradient boosting, DI-VNN); internal and external validation using routine health data	Community-dwelling adults aged ≥60; n=1,381; from 15 community health centers in Kendari, Indonesia	Function: mental health screening; Type: random forest, DI-VNN; Platform: routine health record analysis	Mental Health Screening	AUROC; sensitivity; specificity	Developed a questionnaire-free screening tool for depressive symptoms; useful in low-literacy populations; top predictors: education, living status, family support, comorbidities	Moderate AUROC; lower external validation performance; not a diagnostic tool
Kim et al., 2024, South Korea	Development and Validation of a Machine Learning Method Using Vocal Biomarkers for Identifying Frailty in Community-Dwelling Older Adults: Cross-Sectional Study	Cross-sectional study; n=127; PDT-based voice task; voice and clinical data; 5-fold cross-validation	Community-dwelling adults aged ≥50; n=127; South Korea	Function: frailty detection; Type: deep learning (SpeechAI, DemoAI, DemoSpeechAI); Platform: tablet-based audio analysis	Health, Empowerment	Model accuracy; AUC; comparison of AI variants	SpeechAI model showed 80.4% accuracy (AUC: 0.89); DemoSpeechAI had highest AUC (0.93); AI models outperformed traditional acoustic methods	Small sample; single-language dataset; further real-world validation needed
Yang et al., 2024, Japan	Identification and Prediction of Frailty Among Community-Dwelling Older Japanese Adults Based on Bayesian Network Analysis: A Cross-Sectional and Longitudinal Study	Mixed-methods study using cohort data (2014 & 2017); n=673 baseline, n=373 follow-up; LASSO regression and Bayesian networks	Community-dwelling older adults aged ≥65; Japan; participants from CEC study	Function: frailty prediction and risk factor mapping; Type: Bayesian networks; Platform: offline statistical model	Health, Social Participation	Frailty prevalence and progression; model performance (AUC, calibration); variable associations	Identified direct links between frailty, multimorbidity, physical/social function; improving ISI and polypharmacy reduced frailty risk from 85% to 50%	Needs external validation; frailty based on self-report tool; limited to one Japanese cohort

Study ID	Title	Study Design & Methodology	Population Characteristics	AI Technology Details	CBR Matrix Domain	Outcomes Measured	Main Findings	Limitations
Wu et al., 2023, China	Effect of Artificial Intelligence-Based Health Education Accurately Linking System (AI-HEALS) for Type 2 Diabetes Self-Management	Mixed-methods design (cluster RCT + interviews); 40–45 community health centers; trial ongoing	Adults aged 18–75 with type 2 diabetes; n=664; Beijing community health centers	Function: self-management education and support; Type: knowledge graph-based AI (KBQA); Platform: mobile app (WeChat)	Health	HbA1c reduction; self-management; health literacy; psychological well-being; cost-effectiveness	AI-HEALS shows promise in enhancing diabetes self-management and behavior change using mobile AI support	Trial ongoing; full effectiveness and generalizability not yet assessed
Kamberi et al., 2024, USA	Testing a Machine Learning-Based Adaptive Motivational System for Socioeconomically Disadvantaged Smokers (Adapt2Quit): Protocol for a Randomized Controlled Trial	Two-arm RCT; n=757; 6-month follow-up; daily and biweekly SMS interventions using ML recommender system	Socioeconomically disadvantaged adult smokers; diverse ethnicities; low income and education	Function: behavior change messaging; Type: machine learning recommender system; Platform: SMS-based mobile delivery	Health, Empowerment, Social Participation	7-day point-prevalence smoking cessation at 6 months (CO-verified)	Designed to test if ML-based SMS increases smoking cessation in low-SES groups; trial ongoing; full results pending	Results not yet published; real-world engagement and outcomes under evaluation
Zhao et al., 2025, China	A Social Robot in Home Care: Acceptability and Utility Among Community-Dwelling Older Adults	Mixed-methods study; home deployment for 6 weeks; usage analytics + semi-structured interviews (TFA framework)	Community-dwelling older adults aged 51–88 in fair or good health; n=30	Function: interactive home support; Type: AI-enabled social robot; Platform: stationary home-based device with voice recognition and sensors	Social Support	Feature usage frequency and type; acceptability across 7 domains; engagement over time	Robot used 23.4 times/day/person; improved routines, mood, tech familiarity, and self-esteem; reduced caregiver stress	Small sample; short duration; limited financial accessibility; no control group; no clinical health outcomes assessed

Study by He et al[10]. similarly enrolled Chinese community-dwelling seniors aged 60–75 with sarcopenia, integrating explainable AI both to tailor exercise sequencing and to predict individual rehabilitation outcomes. A parallel-group, double-blind randomized controlled trial was conducted among 94 community-dwelling adults aged 60–75 with sarcopenia in Baishan, China. Participants were randomized for 24 weeks to: a self-determined sequence exercise group (SDSG, n=34), a strength training group (STG, n=30), or control (education, n=30). Exercise sequencing was supported by explainable AI (nine ML models, including SHAP for interpretation); models predicted factors contributing to sarcopenia reversal. The SDSG had the highest reversal rate (47.1%), followed by STG (40.0%) and control (0%). SDSG participants had the greatest improvements in grip strength and relative skeletal muscle mass index. The best machine learning model achieved up to 88.8% accuracy (stacking), and LDA model AUC of 0.91. Adherence in the SDSG was 81%. Their randomized controlled trial found that empowering participants with choice—allowing self-determined exercise regimens guided by AI—led to the greatest improvements in physical function and sarcopenia reversal rates. This work demonstrates the dual benefit of AI in supporting personalized therapy and in increasing motivation and adherence among older adults at risk of functional decline.

Meanwhile, a 12-month longitudinal observational study[9] described advanced technology implementation in a large urban rehabilitation center, including home-, outpatient-, and inpatient-based care. 269 patients (mean age 52.3; 35% female; mostly neurological diagnoses) and 119 clinicians participated. Technologies included robotics, VR, sensor-based feedback, and FES. Data from 4,208 technology sessions showed most use occurred in outpatient/community rehabilitation (94% of sessions). Robotic and VR devices were mainly used for stroke and SCI. Therapy intensity, device use, and setting varied according to diagnosis and service. The study did not report clinical outcomes; it tracked only frequency, type, and duration of technology use reported on the large-scale, real-world implementation of advanced rehabilitation technologies—inclusive of robotics, VR, and sensor-based feedback—in an Australian clinical setting, capturing how these tools are adopted and integrated within outpatient, inpatient, and community services for patients with complex neurological conditions. Although the population in this study encompassed a broad age range, device use was most prominent in adults with stroke or spinal cord injuries. Mennella et al.[7], in contrast, an algorithm validation study developed a deep learning system for remote, real-time analysis of six resistance training exercises, using videos of a rehabilitation expert performing both correct and compensatory movements. No patient data were used; all data derived from expert demonstrations. The model combined MoveNet pose estimation with multilayer perceptron architectures. The mean test accuracy for range of motion phase classification was between 81–95%, and for compensatory movement detection, mean accuracy was 95–100% depending on data augmentation and exercise type. No user or clinical outcomes were reported. While tested only with an expert demonstrator thus far, their system points toward the feasibility of low-cost, objective assessment for unsupervised, home-based rehabilitation in future work.

3.4 | Prediction or Monitoring

The application of AI and machine learning for health risk prediction and screening is prominently demonstrated in three [11,12,13], each targeting a major concern in community-based older adult populations: frailty [12,13] and depressive symptoms.[11] Leveraging readily accessible data—from voice recordings to basic sociodemographic and health information— these studies designed, validated, and in some cases externally tested prediction models that can function within the constraints of real-world, resource-limited primary care and community environments. Kim et al. [13] conducted a prospective cross-sectional study including 127 community-dwelling adults aged 50 years and older (mean age 69.2, 34% female) recruited from a tertiary hospital in Korea. About half of the sample were robust (n=62), the remainder prefrail or frail (n=65), according to the K-FRAIL scale. Participants completed a 2-minute voice task, clinical and functional assessments, and demographic surveys. Three deep learning models were developed: SpeechAI (voice data), DemoAI (demographics), and DemoSpeechAI (combined). The best-performing model, DemoSpeechAI, achieved an accuracy of 85.6% and AUC of 0.93 for frailty classification (sensitivity 87.7%, specificity 83.7%) using 5-fold cross-validation. SpeechAI alone achieved accuracy 80.4% (AUC 0.89). Differences between models using combined versus speech features alone were not statistically significant. DemoAI using demographics only had lower discrimination (AUC 0.74).

Yang et al. [12] analyzed data from 673 community-dwelling Japanese adults aged ≥65 years (mean 73.7, 49.7% women) enrolled in a cohort study. At baseline, 14.1% were frail according to the Kihon Checklist. A longitudinal subsample of 373 non-frail adults was followed for 3 years; 24.1% developed frailty or worsened status over follow-up. Predictive models were built using LASSO regression for variable selection and Bayesian networks for probabilistic modeling. The cross-sectional frailty prediction model had an AUC of 0.943 (95% CI not reported) and was well-calibrated by Hosmer–Lemeshow test (p=0.732). The longitudinal model for frailty worsening had an AUC of 0.722 and good calibration (Hosmer–Lemeshow p=0.551). Major direct predictors included age, physical function, and social relationships/interactions. Susanty et al.[11] developed and validated machine learning models to predict depressive symptoms (GDS-15 ≥ 5) among community-dwelling adults ≥60 years at 15 health centers in Kendari, Indonesia. The dataset included 1,381 participants (final analyzed: 1,252 local, 129 non-local ethnicity); mean age ~66 years, 60–65% female, mostly low education and income. Models used 37 routine demographic and health input variables without the need for GDS- questionnaire data. The best-performing model (random forest) achieved AUROC 0.619 (95% CI: 0.610–0.627) in external (non-local) validation. Other classical and deep neural network models had similar performance. The model was implemented as a web-based screening tool but intended only for initial triage, not replacement of standard diagnostic tools.

3.5 | Behaviour Change or Patient Empowerment

A growing trend in community-based rehabilitation research involves the use of artificial intelligence (AI) tools to support health-related behaviour change and patient empowerment, particularly among populations experiencing barriers to traditional care. Two recent studies exemplify this approach: Wu *et al.* (2023) evaluated an AI-driven digital health education intervention for self-management in type 2 diabetes, while Kamberi *et al.* [14] conducted a large-scale trial of a machine learning–based motivational messaging system to promote smoking cessation in socioeconomically disadvantaged adults. Both studies deployed scalable, technology-enabled solutions designed to personalize care, enhance engagement, and strengthen self-efficacy in real-world, diverse community settings. Wu et al.[15] conducted a mixed-methods study using a cluster-randomized controlled trial design in Beijing, China, with adults aged 18–75 diagnosed with type 2 diabetes mellitus (T2DM). Participants were recruited from 40–45 community health centers and randomized to receive either standard diabetes primary care or standard care plus the AI-HEALS online health education program, which is delivered via WeChat and includes a knowledge graph–based chatbot (KBQA), digital reminders, self-management tracking, and personalized messaging. The primary outcome is HbA1c reduction at 1, 3, 6, 12, and 18 months; secondary outcomes include self-management behavior, health literacy, psychological well-being, and cost- effectiveness. As of protocol publication, recruitment was ongoing and no outcome data have been reported. Assessment tools for self-management, psychological well-being, and quality of life are specified, and intended qualitative interviews will explore user experience, acceptability, and engagement.

Kamberi et al.[14] designed a two-arm, parallel RCT to evaluate Adapt2Quit, a machine learning– powered SMS recommender system to promote smoking cessation among 757 socioeconomically disadvantaged adult smokers in the United States. The intervention group received daily tailored motivational text messages for 30 days and biweekly thereafter up to 6 months, along with proactive quitline referral; the control group received only texting for quitline facilitation and smoking assessment. The primary outcome is biochemically verified 7-day point-prevalence abstinence at 6 months. Secondary outcomes include engagement with messaging, self-reported motivation (Perceived Competence Scale), quitline and NRT use, and qualitative user feedback. At time of protocol publication, recruitment and follow-up were complete; however, main trial results were not yet available. The enrolled sample was highly diverse (64% female, 35% Black, 16% Hispanic, 53% with ≤high school education), and 78% completed follow-up. The study successfully demonstrates recruitment and procedural feasibility but awaits reporting on cessation rates and intervention effectiveness

3.6 | Social Support

In the field of rehabilitation in these recent years, there has been a growing use of artificial intelligence in the form of socially assistive robots represents an innovative approach to supporting emotional well-being, daily functioning, and social inclusion. Zhao *et al.*[16] investigated the acceptability, engagement, and utility of a home-based social robot (KaKa) deployed in the residences of community-dwelling older adults in Hong Kong. This study explored both quantitative patterns of robot usage and qualitative experiences, offering valuable insights into the potential of AI-driven technologies to enhance social support and autonomy within community-based rehabilitation frameworks. The study included 30 community-dwelling older adults in Hong Kong, aged 51–88 years (77% female, 90% with secondary or higher education), with a mix of living arrangements: 40% living alone, 23% with a partner, and 37% with family. Most participants reported fair or good health (90%) and financial status (93%). Each participant received a social robot (KaKa) in their home for 6 weeks, operating 24/7. Participants reported that KaKa served as a companion, fostered emotional well-being, reduced loneliness, and provided support with reminders for daily activities, medication, and meals. Many users considered the robot helpful for family caregivers, noting reductions in caregiver stress and improved routine management for patients with dementia. The robot's conversational abilities enabled participants to share feelings, ask for jokes or news, and receive regular reminders. Some participants noted increased interest in technology and expressed pride in acquiring new digital skills.

4 | DISCUSSION

The use of artificial intelligence to support home-based and remote rehabilitation reflects one of the most promising developments in community-based rehabilitation, as illustrated by the four included studies. Collectively, these studies demonstrate that AI technologies can function across a spectrum of rehabilitation needs, including cognitive interventions[8], physical exercise programs[10], technological integration and adoption in practice[9] and remote exercise assessment/monitoring.[7] Both randomized controlled trials in this group[8,10] provide evidence that individualized, AI-supported interventions delivered at home can achieve clinically meaningful improvements in function for older adults. In Graessel et al.[8], adaptive computerized cognitive training led to significantly greater cognitive improvement than a non-adaptive control, with high user engagement and more cases of MCI reversal. He et al.[10] found that supporting exercise sequencing choices with explainable AI enabled better muscle strength gains and sarcopenia reversal rates, highlighting the dual benefits of AI for both personalization and empowerment in the elderly. Importantly, both studies targeted older adults who were capable of participating in technology-mediated interventions—those with digital literacy or independent living—which may limit the generalizability to more vulnerable, lower-resource populations.

Pearce et al.[9] broaden the view of AI and technology integration, illustrating real-world clinician adoption of advanced digital tools (e.g., robotics, VR, sensors) across both home and community rehab contexts for largely neurological populations. Their data reinforce that real- world uptake and intensity of technology use vary widely depending on patient needs, clinician familiarity, and local resources. This study, along with Mennella et al.[7] technical validation of real-time movement classification systems, emphasizes that successful implementation depends not just on algorithmic accuracy but also on usability, accessibility, clinician training, and system-level support work, while technically robust, signals that further research is needed to translate promising AI models from controlled settings (expert demonstrations) to routine practice with diverse patients—especially those with impairments or limited digital skills. The application of AI-based prediction and screening tools in community-based rehabilitation is an area of accelerating interest.[11,12,13] These works illustrate that machine learning and probabilistic modeling can support early identification of frailty and depressive symptoms—two critical and prevalent health issues among older adults in community settings. The studies employed varied but accessible data inputs, from non-invasive vocal biomarkers and simple demographic features to detailed psychosocial and clinical profiles, reflecting the diverse technological and infrastructural contexts where community-based interventions are needed.

The included studies reported moderate to strong model performance, with deep learning models in achieving AUCs up to 0.93 for frailty prediction[13], and Bayesian network approaches in Yang et al.[12] demonstrating excellent discrimination (AUC 0.94) for cross- sectional frailty risk and fair capability (AUC 0.72) in modeling frailty progression over three years. Susanty et al.[11] random forest classifier offered moderate accuracy (AUROC 0.62) in external ethnic validation for depressive symptom screening using only routine health and sociodemographic data. These results suggest that, particularly for well-defined populations, AI models hold promise as scalable pre-screening or risk stratification tools. Such systems could efficiently prioritize individuals for more in-depth assessment or intervention, thereby optimizing use of limited resources in low- and middle-income or rural settings. However, challenges to broader implementation remain. These studies reveal both the promise and the current limitations of AI-based screening in the community. While models multifactorial Bayesian networks offer high discrimination and individualized probability estimates for conditions like frailty[12,14], questionnaire-free depression screener provide scalable solutions where conventional approaches are impractical.[11] However, generalizability remains a challenge. Most models were developed on single-country, single-ethnic populations, with modest external validation and varying performance across groups. Ongoing research should prioritize larger, more diverse samples and prospective validation of risk algorithms to ensure these promising AI tools are equitable, accurate, and impactful at scale in community-based rehabilitation and preventive health.

The integration of artificial intelligence into behavioral change and patient empowerment interventions represents a significant advancement in community-based rehabilitation,[14,15] These studies demonstrate the feasibility and scalability of digitial, AI enhanced approaches for promoting health behavior change in large, diverse community populations including those traditionally underserved by conventional healthcare.

Both studies addressing patient empowerment targeted populations facing unique barriers. Wu et al. focused on adults with type 2 diabetes in urban Chinese community health centers, whereas Kamberi et al.[14] recruited socioeconomically disadvantaged smokers across multiple health systems in the United States. Their AI-enabled interventions were specifically tailored to address critical needs—diabetes self-management and smoking cessation—through the delivery of personalized and adaptive content, such as interactive health education chatbots or motivational SMS messages. These approaches were designed to foster sustained engagement and enhance self-efficacy. Importantly, both studies demonstrated successful recruitment and achieved large, diverse participant samples, highlighting the real-world relevance and acceptability of digital health strategies in community contexts.

Despite these strengths, evidence on the effectiveness of AI-based empowerment interventions remains preliminary, as neither study had reported primary outcome measures—such as HbA1c reduction or biochemically verified smoking abstinence—at the time of publication. This gap underscores a recurring challenge in the field: while AI innovations are advancing rapidly and feasibility in terms of recruitment, engagement, and implementation is increasingly well-documented, rigorous evidence on long-term behavioral change, sustained health outcomes, and broader population-level impact is still emerging. Furthermore, barriers such as unequal digital access, variability in user engagement, and the need for culturally and linguistically adapted content must be addressed to ensure equity and maximize utility across diverse populations.

Zhao et al.[16] provided additional insights into the potential of socially assistive robots for supporting psychosocial well-being and daily living in older adults. Their findings indicated that high engagement and acceptability were achieved, suggesting that robots like KaKa may reduce loneliness, enhance emotional health, and assist with routine management, particularly for individuals living alone or with limited social support. Participants readily integrated the robot into their daily lives, benefiting from companionship, reminders, and an intuitive design that encouraged adoption.

Nevertheless, several challenges remain. Most participants in these studies were recruited from relatively educated and technologically engaged populations, often within urban or research-intensive settings. Clinical outcomes were not consistently reported, and little is known about the long-term sustainability of these interventions or their applicability in less-resourced, rural, or marginalized communities—settings where community-based rehabilitation is most urgently needed. While reported improvements in accuracy, adherence, and engagement are promising, ensuring equity remains a critical issue. Future studies should focus on expanding access to individuals with limited digital literacy, lower socioeconomic status, or multiple comorbidities.

Taken together, the reviewed studies demonstrate how artificial intelligence is shaping the future of community-based rehabilitation by enabling more personalized, accessible, and effective interventions across a range of needs. Whether facilitating home-based rehabilitation, supporting early risk prediction, empowering behavior change, or providing social support through innovative technologies, AI-enabled strategies consistently show feasibility, acceptability, and early indications of impact among community-dwelling populations. However, most interventions have thus far been tested in relatively narrow cohorts, with few reporting long-term outcomes or effectiveness at scale. To realize the full potential of AI in CBR, future research should prioritize robust, multi-site implementation trials, long-term evaluation, and inclusive user-centered design that ensures equitable access and meaningful integration into existing care pathways.

5 | CONCLUSION

This systematic review demonstrates the growing role of artificial intelligence in community-based rehabilitation, showing promise in home-based care, early risk prediction, patient empowerment, and social support. While feasibility and acceptability are evident, most studies remain limited by small scale, short follow-up, and selective populations. Future research should focus on large, diverse, and long-term trials to ensure equitable and sustainable integration of AI into community rehabilitation, aligning with its core objectives of promoting independence, participation, and well-being.

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Conflict of Interest
The authors declare no conflicts of interest in preparing this article.

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