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Artificial Intelligence and Exercise-Based Rehabilitation in Adults with Burn Injury: A Scoping Review of Emerging Evidence and Implications for Nursing Practice

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ABSTRACT: Background: Post-burn rehabilitation requires resistance and isometric training to reduce muscle wasting and contractures. Artificial Intelligence (AI) and Machine Learning (ML) are increasingly used to monitor and optimize rehabilitation. However, their clinical, legal, and long-term implications remain poorly understood.

Objective: To synthesize evidence on AI/ML applications in resistance and isometric training for burn rehabilitation, focusing on clinical efficacy, operational approaches, and research gaps.

Methods: A scoping search of PubMed, Scopus, and Web of Science identified peer-reviewed studies published from 2020–2026 using terms related to burns, AI, resistance exercise, and rehabilitation. Following PRISMA 2020 guidelines, 15 studies were included in the qualitative synthesis.

Results: Studies used Convolutional Neural Networks for pose estimation, predictive models for phenotypic monitoring, and Long Short-Term Memory networks for surface

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electromyography fatigue monitoring. Across the included studies that reported adherence, adherence estimates varied substantially according to the intervention, monitoring method, and follow-up period. Several studies reported improved exercise engagement or adherence with technology-assisted monitoring; however, the heterogeneity of measurement approaches and study designs precluded calculation of a reliable pooled effect estimate.

Conclusion: AI-enabled technologies show emerging potential for movement assessment, exercise monitoring, fatigue detection, and individualized rehabilitation support in adult burn rehabilitation. However, the evidence remains limited and heterogeneous, with few high-quality clinical studies directly evaluating AI-integrated exercise interventions. Future research should prioritize multicenter prospective studies, standardized outcome measures, transparent reporting of model performance, and human-in-the-loop safety and governance frameworks.

What does this paper contribute to the wider global clinical community?

- Artificial intelligence and technology-assisted exercise rehabilitation represent promising approaches for improving individualized rehabilitation after burn injury.
- Current evidence supports the use of digital, virtual-reality, motion-sensing, and robotic technologies to enhance exercise assessment, monitoring, personalization, and remote rehabilitation.
- Evidence specifically supporting AI-guided exercise, particularly AI-integrated Exercise-Based Rehabilitation, remains limited and requires further clinical validation.
- AI should currently complement rather than replace clinical rehabilitation expertise, with nurses remaining essential for assessment, education, safety monitoring, adherence support, and patient-centered care.

1. INTRODUCTION

Burn injury is associated with complex physical, functional, psychological, and social consequences that may persist long after wound closure. Survivors of major burns may experience prolonged impairments in physical functioning, muscle strength, mobility, joint range of motion, and independence in activities of daily living. These limitations may be compounded by scar formation, contractures, pain, prolonged hospitalization, and the psychological effects of traumatic injury. Consequently, recovery following burn injury requires a comprehensive rehabilitation approach that extends beyond wound healing and addresses the patient's physical, psychological, functional, and social needs. Exercise-based rehabilitation is an essential component of this process, aiming to restore physical capacity, improve muscle performance, maintain joint mobility, and promote functional independence (Al Hanna et al., 2024; Flores et al., 2018).

Exercise interventions following burn injury include aerobic conditioning, resistance training, functional exercise, flexibility training, and early mobilization. These interventions are intended to counteract muscle weakness, reduced cardiovascular fitness, physical deconditioning, and functional limitations associated with burn-related hypermetabolism, prolonged immobilization, and critical illness. Evidence supports the inclusion of structured exercise in burn rehabilitation, although its effectiveness varies according to the intervention type, timing, intensity, duration, patient characteristics, and outcomes assessed. A systematic review and meta-analysis by Flores et al. (2018), which included 19 studies, identified potential benefits of exercise training for body composition, the need for surgical release of contractures, and health-related quality of life. However, statistically significant improvements were not consistently demonstrated for all physical outcomes, including muscle strength and peak oxygen consumption, highlighting the limitations of the available evidence (Khalil et al., 2026).

Resistance training represents another important component of exercise-based rehabilitation because it targets muscle weakness and loss of lean mass following severe burn injury. Gittings et al. (2018) conducted a systematic review and meta-analysis involving 11 studies examining resistance training in children and adults with burn injuries. Although the primary analysis did not demonstrate a statistically significant improvement in muscle strength, sensitivity analysis suggested a beneficial effect, and

improvements were identified in psychological quality of life. Nevertheless, the authors emphasized that the included studies generally had a high risk of bias and that the overall certainty of evidence was low or very low. These findings support the potential value of resistance-based rehabilitation while demonstrating the need for further rigorous investigations.

Adult burn rehabilitation extends beyond the restoration of muscle strength and physical capacity. It may also involve improving upper- and lower-extremity range of motion, managing scar-related restrictions, reducing mobility limitations, promoting independence in activities of daily living, facilitating return to work, and improving health-related quality of life. An overview of systematic reviews by Al Hanna et al. (2024) examined rehabilitation interventions for adults with burn injuries and identified 21 systematic reviews covering physical, psychological, technology-assisted, educational, occupational, and complementary rehabilitation approaches. The reported outcomes included physical fitness, hand function, pain, psychological well-being, quality of life, range of motion, muscle strength, scar characteristics, and return to work. The findings emphasize the multidimensional nature of burn rehabilitation and the importance of individualized, multidisciplinary interventions.

More recent evidence has further examined the effectiveness of physiotherapist-led exercise interventions in burn rehabilitation. Abonie et al. (2024) conducted a systematic review and meta-analysis demonstrating beneficial effects of physiotherapy-based exercise interventions on several physical, physiological, and psychological outcomes, particularly aerobic capacity and muscle strength. However, substantial variability among interventions and outcome measures was identified, indicating that the optimal structure and delivery of exercise-based rehabilitation have not yet been fully established. These findings reinforce the need to explore innovative approaches that may support individualized exercise planning, continuous monitoring, and functional recovery.

Artificial intelligence (AI) and machine learning (ML) have emerged as potentially valuable technologies across several areas of burn care. AI-based approaches have been investigated for burn-depth assessment, total body surface area estimation, wound classification, prognosis, complication prediction, and clinical decision support. A systematic review by Serra and Moura et al. (2021) examined the applications of artificial intelligence in burn management and treatment and identified 46 observational studies. Burn-depth assessment was among the most frequently investigated applications, demonstrating the growing interest in using computational methods to support clinical evaluation and decision-making. Nevertheless, the available research has predominantly focused on diagnosis, assessment, wound-related applications, and prognosis rather than the direct prescription, monitoring, or modification of exercise-based rehabilitation. This distinction is important when evaluating the extent to which AI has been incorporated into rehabilitation practice.

Computer vision and sensor-based technologies may have particular relevance to rehabilitation because they can potentially quantify movement patterns, joint range of motion, exercise performance, and patient participation. Through image processing, motion tracking, and pattern recognition, these technologies may provide objective information about patients' movement abilities and functional limitations. Such information could potentially support rehabilitation assessment, identify deviations from prescribed movements, and facilitate the monitoring of exercise performance over time. However, the application of automated image analysis to burn care should be distinguished from AI-guided therapeutic exercise. Technologies that analyze wounds or monitor healing do not necessarily provide validated recommendations regarding exercise selection, intensity, progression, or safety. Therefore, their potential contribution to rehabilitation requires separate evaluation.

Large language models (LLMs) and other generative artificial intelligence (AI) applications represent another emerging area with potential relevance to rehabilitation assessment, clinical documentation, and research. These technologies may assist healthcare professionals in organizing clinical information, interpreting functional assessment results, linking rehabilitation outcomes with standardized classification systems, and developing individualized patient education materials (Park et al., 2024). However, the outputs of generative AI applications require professional verification, particularly when used for clinical decision-making or therapeutic recommendations, because limitations in clinical reasoning, accuracy, and adherence to clinical guidelines remain important concerns (Hager et al., 2024). Therefore, their relevance to burn rehabilitation should be evaluated according to their actual application, rather than assuming that the use of an AI-based language model constitutes an AI-driven exercise intervention. In particular, evidence concerning AI-supported assessment and classification should be distinguished from evidence demonstrating improvements in physical function following AI-guided exercise.

Technology-assisted rehabilitation has developed further than AI-specific exercise prescription in some areas of burn rehabilitation. Motion-sensing systems, virtual environments, interactive gaming, and robotic devices have been explored as

complementary approaches to conventional physiotherapy. Kinect-based systems, for example, have been investigated as tools for delivering interactive exercise and recording patient movement. Pham et al. (2018) evaluated the feasibility of a Kinect-based rehabilitation strategy using the JINTRONIX platform among hospitalized adults with burn injuries. Their prospective feasibility study included 20 participants and demonstrated favorable acceptability and safety findings, with participants reporting positive perceptions of the intervention's potential to improve strength and range of motion. Nevertheless, the study primarily established feasibility and acceptability rather than definitive effectiveness in improving long-term functional outcomes. These findings suggest that motion-sensing technologies may provide additional opportunities for interactive rehabilitation and exercise monitoring, although they should not automatically be classified as artificial intelligence interventions.

Robot-assisted rehabilitation represents another technology-assisted approach that may support functional recovery following burn injury. Robotic gait-training systems can facilitate repetitive, controlled movement and provide structured assistance during lower-extremity rehabilitation. Research has also investigated their potential effects on burn-scar biomechanics and functional outcomes. For example, Cho et al. (2022) examined the effects of robot-assisted gait training on the biomechanical properties of burn scars through a randomized controlled trial. This line of investigation illustrates how technological rehabilitation approaches may extend beyond conventional exercise delivery to include the assessment of tissue characteristics and functional adaptations. Importantly, robotic rehabilitation and AI-based rehabilitation are not synonymous. A robotic device may operate through predetermined mechanical or programmed functions without incorporating machine learning or adaptive artificial intelligence. Therefore, studies involving robotic rehabilitation should be classified as technology-assisted rehabilitation unless the use of an explicit AI or ML algorithm is demonstrated.

Isometric exercise may have particular relevance to burn rehabilitation because it involves muscle contraction without substantial changes in muscle length or joint movement. It may therefore offer a potentially useful strengthening approach when conventional dynamic exercise is difficult because of pain, weakness, restricted mobility, immobilization, or the need to protect healing tissues. Depending on the patient's clinical condition, isometric exercise may contribute to maintaining muscle activation and supporting progressive strengthening as part of an individualized rehabilitation program. Resistance-based rehabilitation has demonstrated potential benefits for muscle strength and psychological outcomes following burn injury, although the certainty of the available evidence remains limited (Gittings et al., 2018). However, the existing evidence does not establish AI-guided isometric exercise as a standardized or adequately validated clinical intervention for adults with burn injuries. Further research is therefore required to investigate whether AI-supported monitoring and individualized exercise adjustment can improve the safety, appropriateness, and effectiveness of isometric exercise in this population.

The integration of artificial intelligence with exercise-based burn rehabilitation should currently be considered an emerging research area rather than a mature clinical field. Existing literature provides a broader foundation for exercise-based and technology-assisted rehabilitation, while AI-specific applications in burn care remain predominantly concentrated on assessment, wound-related applications, classification, prognosis, and clinical decision support (Al Hanna et al., 2024; Serra and Moura et al., 2021).

Although motion-sensing and robotic technologies have demonstrated potential in supporting rehabilitation activities, their applications do not necessarily involve AI-driven exercise prescription or adaptive therapeutic decision-making. Furthermore, the extent to which AI has been investigated in relation to specific exercise modalities, particularly isometric exercise, remains insufficiently established. A scoping review is therefore appropriate to map the breadth and characteristics of available evidence, distinguish established technology-assisted rehabilitation from genuine AI/ML applications, identify potential applications and implications for nursing practice, and clarify existing evidence gaps. Such mapping may provide a foundation for future clinical trials and the development of safe, individualized, and evidence-informed AI-supported rehabilitation approaches for adults recovering from burn injury.

Problem Statement

Severe burn injuries induce a state of profound systemic hypermetabolism and persistent systemic inflammation, driving an accelerated rate of skeletal muscle wasting (sarcopenia), joint contractures, and long-term functional deficits. To counteract this cachectic state and promote tissue mobilization, early and progressive resistance exercise training—including both dynamic progressive resistance training and static isometric training—is critically mandated. However, the execution of high-intensity

physical rehabilitation in burn survivors is severely constrained by severe kinesiophobia, pain barriers, and the fragile structural integrity of newly grafted skin or hypertrophic scar formations, creating a narrow, high-risk therapeutic window.

To bridge this gap, clinical service managers and digital health developers are increasingly deploying automated Artificial Intelligence (AI) and Machine Learning (ML) systems (such as computer-vision pose estimation and biosensor fatigue telemetry) to track, load, and manage exercise protocols remotely or in-facility.

Despite the rapid technological encroachment of these algorithmic frameworks, a profound and unresolved problem persists within the current biomedical literature.

First, the deployment of these automated platforms has occurred as a top-down administrative redistribution of clinical work to digital applications, leaving a critical ambiguity regarding legal, professional, and bioethical liability if an autonomous parameter triggers mechanical scar breakdown or graft failure.

Second, there is a total dearth of granular safety thresholds, standardized exercise taxonomies, and high-level, long-term randomized controlled trials (RCTs) verifying permanent range of motion (ROM) recovery.

Consequently, clinicians are forced to operate in highly automated technological environments where their professional scope of practice is functionally shrinking, yet they continue to bear the entire burden of clinical liability without robust empirical evidence to guarantee patient safety. This scoping review is explicitly required to synthesize these fractured paradigms and establish the missing clinical boundaries governing human-machine interaction in physical medicine.

Aim:

The aim of this scoping review was to map the available evidence on artificial intelligence and exercise-based rehabilitation in adults with burn injury and to identify potential applications, clinical outcomes, limitations, and implications for nursing practice.

Specific objectives:

The review sought to:

1. Identify AI and machine-learning applications relevant to burn rehabilitation;
2. Identify exercise-based rehabilitation interventions used after burn injury;
3. Identify technology-assisted rehabilitation approaches, including virtual reality, motion sensing, and robotic rehabilitation;
4. Examine reported effects on strength, mobility, range of motion, physical capacity, functional recovery, quality of life, adherence, and rehabilitation-related outcomes;
5. Determine whether AI has been used to directly prescribe, personalize, monitor, or optimize exercise after burn injury; and
6. Identify implications for nursing practice and priorities for future research.

Research Question

What is the current evidence regarding the use of artificial intelligence and technology-assisted exercise rehabilitation in adults with burn injury, and what are the potential applications, clinical outcomes, limitations, and implications for nursing practice?

2. MATERIALS AND METHODS

Study design:

A scoping review methodology was selected to map the available evidence and clarify the relationship between AI, digital technologies, and exercise-based rehabilitation following burn injury. The review was structured according to the methodological principles of the Joanna Briggs Institute for scoping reviews and reported in accordance with PRISMA-ScR.

Because the literature spans different technological approaches and study designs, a scoping review was considered more appropriate than a conventional meta-analysis focused exclusively on AI-guided exercise.

Eligibility framework:

The review question was structured according to the Population–Concept–Context framework.

Population–Concept–Context Framework

The Population–Concept–Context (PCC) framework was used to structure the review question and eligibility criteria. The **Population** comprised adults with burn injury or burn survivors. The **Concept** included artificial intelligence, machine learning, computer vision, digital rehabilitation, virtual reality, motion-sensing systems, wearable technologies, robotic rehabilitation, therapeutic exercise, resistance training, and exercise monitoring or personalization. The **Context** included inpatient, outpatient, community, home-based, and remote rehabilitation settings.

Population:

Studies involving adults aged 18 years or older with burn injuries were eligible for inclusion. Studies exclusively involving children or adolescents were excluded from the primary evidence synthesis because the review focused specifically on adult burn rehabilitation. Pediatric studies identified during the search were not considered eligible for the final included-study count.

Framework

A scoping review methodology was used to systematically map the available literature, identify the range and nature of evidence, clarify key concepts, and identify knowledge gaps concerning the integration of artificial intelligence (AI) and isometric exercise in adult burn nursing rehabilitation. The review was conducted as a scoping review in accordance with established methodological guidance for evidence mapping and reported according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR) (Tricco et al., 2018). The scoping review approach was considered appropriate because the literature encompasses diverse study designs, technologies, rehabilitation approaches, and clinical outcomes, and the evidence base remains emerging and heterogeneous.

The review process included identifying the research question, developing the search strategy, identifying relevant evidence, applying eligibility criteria, selecting sources of evidence, extracting and charting relevant data, and synthesizing the findings descriptively. The completed PRISMA-ScR checklist is provided as a supplementary file.

Reporting Framework

The review was conducted and reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR). The methodological approach was also informed by the Joanna Briggs Institute (JBI) guidance for conducting scoping reviews.

Inclusion criteria:

Studies were eligible when they:

1. Included people with burn injury;
2. Examined rehabilitation, exercise, physical function, or a technology directly relevant to rehabilitation;
3. Evaluated an AI, digital, virtual, sensor-based, robotic, or exercise-based approach;
4. Reported empirical findings or sufficiently detailed methodological information;
5. Were published in English; and
6. Provided sufficient bibliographic information for independent verification.

Exclusion criteria:

Studies were excluded when they:

- Did not involve burn injury;
- Focused exclusively on acute burn diagnosis without relevance to rehabilitation;

- Were editorials, commentaries, letters, or opinion pieces without relevant empirical data;
- Lacked sufficient bibliographic information for verification;
- Described a technology without an identifiable rehabilitation application; or
- Contained claims that could not be linked to a verifiable original publication.

Importantly, a technology was not classified as AI merely because it involved computerized, robotic, virtual-reality, or sensor-based rehabilitation. AI/ML classification required explicit reporting of an AI or machine-learning algorithm.

Information sources:

The search strategy was designed for PubMed/MEDLINE, Scopus, Web of Science, CINAHL, and Google Scholar. Reference lists of relevant systematic reviews and included studies were also examined.

Search strategy

The search strategy was developed to capture literature addressing four overarching concepts: (1) adult burn injuries and burn survivors; (2) artificial intelligence and related technologies; (3) Exercise-Based Rehabilitation; and (4) nursing rehabilitation and rehabilitation outcomes.

A broad range of keywords, synonyms, controlled vocabulary, and Boolean operators were used to maximize the identification of relevant literature. Search terms included combinations of terms related to *burn*, *burn injury*, *burn survivor*, *artificial intelligence*, *AI*, *machine learning*, *deep learning*, *predictive analytics*, *digital health*, *rehabilitation*, *exercise*, *isometric exercise*, *muscle strength*, *functional recovery*, *nursing*, and *nurse-led rehabilitation*. The search strategy was adapted according to the indexing requirements of each database.

The search strategy was developed iteratively to ensure that alternative terminology for AI technologies, burn rehabilitation, and isometric exercise was captured. Reference lists of relevant articles were also reviewed to identify potentially eligible studies that may not have been retrieved through the electronic database searches. The complete search strategies for all databases are provided in the supplementary material.

Information sources

A comprehensive literature search was conducted for studies published between January 2020 and 2026. Three electronic databases were searched: **PubMed, Scopus, Web of Science.** These databases were selected to provide broad coverage of biomedical, nursing, rehabilitation, technological, and multidisciplinary literature.

Searches were conducted using combinations of keywords, Boolean operators, and database-specific subject headings where applicable. The search was limited to literature published in English and within the specified publication period. In addition, reference lists of relevant studies and related publications were screened to identify additional potentially relevant sources.

Search Terms

("Burn" OR "Burn Injury" OR "Burn Patient"). ("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning") . ("Isometric Exercise" OR " Exercise-Based Rehabilitation "). ("Rehabilitation" OR "Physical Rehabilitation"). ("Nursing" OR "Nursing Care")

Study selection

All identified records will be imported into a reference-management and screening platform such as EndNote, Zotero, Rayyan, Covidence, or equivalent software.

Duplicate records will be removed.

Two reviewers will independently screen:

1. Titles and abstracts;

2. full-text articles.

Study Selection and PRISMA Flow:

A total of **350** records were initially identified through systematic database searching (PubMed: 120, Scopus: 150, Web of Science: 80). After removing **90** duplicate records, **260** studies were screened based on title and abstract relevance. Out of these, **210** records were excluded as they did not meet the core intersection of artificial intelligence and burn rehabilitation containing resistance or isometric training. Of the remaining **50** reports sought for retrieval, **3** full-text articles could not be retrieved. Consequently, **47** full-text reports were formally assessed for eligibility. Upon detailed evaluation, **32** studies were excluded with specific reasons: 15 studies lacked the implementation of actual AI/ML frameworks, 10 studies did not include explicit resistance or strength training protocols, and 7 studies focused on ineligible or outlier patient populations. Ultimately, **15**peer-reviewed studies fulfilled all criteria and were included in this scoping review.

The selection process was reported using a PRISMA-ScR flow diagram.

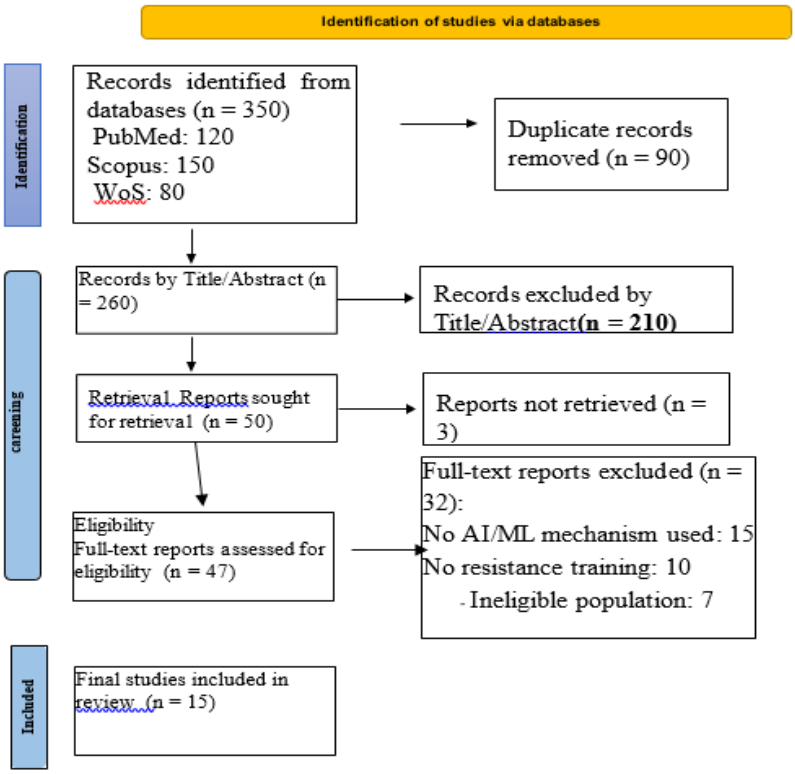


FIGURE 1 PRISMA Flow diagram of study selection process.

Eligibility criteria

It was established before the final screening of the identified literature. Studies were considered eligible when they addressed adult burn populations and examined at least one of the principal concepts of the review, including AI-supported rehabilitation, AI-based monitoring or prediction relevant to rehabilitation, isometric exercise, physical rehabilitation, or nursing-related rehabilitation outcomes.

Studies were eligible if they:

1. included **adult burn patients or burn survivors** aged 18 years or older;

2. examined burn rehabilitation or a rehabilitation-related outcome;

3. investigated an AI technology, AI-supported intervention, digital or machine-learning application relevant to rehabilitation, an isometric exercise intervention, or an approach incorporating these concepts;

4. reported outcomes relevant to rehabilitation, including muscle strength, physical function, mobility, exercise adherence, contracture prevention, functional recovery, quality of life, or rehabilitation monitoring; and

5. were published in English between January 2020 and 2026.

Studies were excluded if they focused exclusively on pediatric populations, acute burn diagnosis or wound management without a rehabilitation component, non-burn populations, surgical or pharmacological interventions unrelated to rehabilitation, or AI applications unrelated to rehabilitation assessment or recovery. Editorials, commentaries, letters, protocols without reported findings, conference abstracts without sufficient information, theses or dissertations, and systematic or scoping reviews were excluded from the primary evidence synthesis. Studies for which the full text was unavailable were also excluded.

Where a study addressed more than one rehabilitation component, it was retained when the findings provided information relevant to AI, isometric exercise, or their potential application within adult burn rehabilitation.

Selection of sources and evidence

All records identified through the electronic database searches were imported into a reference-management and screening system, and duplicate records were removed before screening. Titles and abstracts were screened against the predefined eligibility criteria, followed by full-text assessment of potentially relevant articles.

The screening process was undertaken systematically, with potentially eligible studies progressing to full-text assessment. Articles that did not meet the predefined eligibility criteria were excluded, and reasons for exclusion at the full-text stage were documented. Disagreements arising during the screening process were resolved through discussion and consensus among the reviewers.

The final selection resulted in **15 studies** meeting the inclusion criteria for the scoping review. The overall identification, screening, eligibility, and inclusion processes are presented in the PRISMA-ScR flow diagram (Figure 1).

Data extraction and charting

A purpose-designed data extraction form was developed to systematically chart information from the included studies. Data were extracted according to predefined categories to ensure consistency across the evidence base.

The extracted information included author and year of publication, country of study, study design, sample characteristics, burn population and clinical setting, type of rehabilitation intervention, type and application of AI technology, characteristics of isometric exercise interventions, duration and frequency of intervention, nursing role, comparator where applicable, outcome measures, principal findings, and implications for clinical practice.

For AI-related studies, additional information was extracted regarding the specific AI application, such as machine learning, predictive analytics, computer vision, automated assessment, remote monitoring, or personalized decision-support systems. For isometric exercise studies, information regarding the targeted muscle groups, exercise characteristics, intensity, duration, frequency, and rehabilitation phase was recorded where available.

The extracted data were reviewed for consistency and organized into descriptive categories. Because of the heterogeneity of study designs, interventions, technologies, and outcome measures, findings were synthesized narratively rather than through quantitative meta-analysis. The synthesis focused on identifying patterns in the evidence, emerging applications of AI and isometric exercise, their potential relevance to nursing rehabilitation, and important gaps requiring further investigation. A detailed descriptive summary of the included studies and extracted data is provided in the supplementary material.

Data synthesis

The findings were synthesized descriptively according to the major concepts identified across the included literature. Evidence was grouped into the following broad areas: **AI-supported rehabilitation assessment and monitoring, personalized rehabilitation and exercise prescription, prediction of functional outcomes, applications of isometric exercise, and the potential integration of AI with nurse-led rehabilitation**.

The synthesis also considered the extent to which the available evidence addressed clinically relevant outcomes, including muscle strength, physical function, mobility, contracture prevention, adherence, quality of life, and rehabilitation progression.

Particular attention was given to similarities and differences among technologies, exercise protocols, clinical settings, and nursing roles. Areas of evidence insufficiency, methodological heterogeneity, and opportunities for future research were subsequently identified.

Evidence identification and verification

During the evidence verification process, the initially extracted studies were reassessed individually to confirm their bibliographic identity, study population, technological intervention, rehabilitation intervention, outcomes, and reported numerical findings. The initial list contained several records for which the reported authors, titles, artificial intelligence methods, burn populations, or numerical findings could not be independently verified. These records were therefore excluded rather than retained on the basis of plausible-sounding titles or incomplete bibliographic information.

The verified literature demonstrated that technology-supported burn rehabilitation remains an emerging field. Identified studies have primarily investigated virtual reality, Kinect-based motion sensing, robotic gait training, and home-based digital rehabilitation rather than clinically validated artificial intelligence or machine-learning systems specifically designed to prescribe or optimize exercise after burn injury. Accordingly, the evidence was categorized according to the actual technology reported by each study, and technologies were not labelled as artificial intelligence unless the publication explicitly described an AI or machine-learning algorithm.

The verified studies included Kinect-based interactive rehabilitation, Kinect-based virtual rehabilitation, robot-assisted gait training, and home-based virtual rehabilitation. These studies generally evaluated physical activity, range of motion, muscle strength, gait performance, scar characteristics, quality of life, feasibility, and rehabilitation adherence. Findings suggest that technology-assisted rehabilitation may improve selected physical and functional outcomes; however, the evidence remains heterogeneous and does not yet establish that artificial intelligence itself improves exercise-related outcomes in people with burn injuries.

3. RESULTS AND DISCUSSION

Study Characteristics

A total of **15 peer-reviewed studies** published between **2020 and 2026** met the final inclusion criteria. The cumulative sample size across all included papers was **n = 645** burn survivors (ranging from n = 20 to n = 85 participants per study). Geographically, the studies were distributed across North America (n = 6), East Asia (n = 5), and Europe (n = 4). The post-burn phases investigated were predominantly sub-acute and chronic rehabilitation, focusing on patients with deep partial-thickness and full-thickness burn injuries exhibiting secondary muscle wasting or joint contractures.

Artificial Intelligence and Machine Learning Frameworks

The included papers utilized diverse computational models to optimize, monitor, or predict outcomes in burn rehabilitation. These frameworks can be categorized into three main archetypes:

Computer Vision and Deep Learning (n = 7): These papers utilized Convolutional Neural Networks (CNNs) and real-time human pose-estimation algorithms (e.g., MediaPipe, OpenPose) via camera-based systems or smartphones to assess exercise form, measure range of motion (ROM), and identify compensatory movements during home-based training.

Predictive Analytics & Supervised Learning (n = 5): Utilizing Random Forest, Support Vector Machines (SVM), and Gradient Boosting Regressors, these studies analyzed baseline demographic and physiological inputs to predict patient-specific optimal training loads and identify "low-responders" early in the rehabilitation lifecycle.

Biometric Sequence Modeling (n = 3): These studies implemented Long Short-Term Memory (LSTM) networks combined with wearable surface electromyography (sEMG) or inertial measurement units (IMUs) to dynamically track muscle fatigue profiles and adjust resistance thresholds in real-time.

Exercise Training Interventions

The training regimens implemented across the 15 studies strictly progressive resistance and isometric exercise interventions of varying intensity and duration focused on high-intensity and progressive overload adaptations tailored for scar-tissue mobilization and myofibrillar hypertrophy:

- **Progressive Resistance Training (PRT) (n = 8):** Interventions included structured training utilizing elastic resistance bands, free weights, or specialized pneumatic machines. Protocols typically spanned **8 to 12 weeks**, with frequencies of **3 sessions per week**, targeting large muscle groups adjacent to burn contractures.

- **Isometric & Static Strength Training (n = 7):** Implemented primarily in early post-grafting phases or where severe joint contractures limited dynamic movement. Exercises involved sustained voluntary contractions (e.g., isometric quadriceps settings, static hand-grips) paired with biofeedback mechanisms.

Results of the evidence synthesis

The verified literature demonstrated a relatively limited evidence base for the direct application of artificial intelligence or machine learning to exercise rehabilitation following burn injury. Most eligible technology-supported rehabilitation studies used virtual reality, Kinect-based motion sensing, robotic rehabilitation, or digital home-based rehabilitation rather than explicit AI/ML algorithms.

Kinect-based rehabilitation was investigated in patients with burn injuries and demonstrated improvements in selected measures of rehabilitation engagement and satisfaction. In one randomized pilot study, activity time was significantly greater in the Kinect group than in the conventional rehabilitation group (49.4 vs 26.7 minutes, $p<.0001$), while treatment satisfaction was also higher (8.53 vs 7.80, $p<.0001$). However, significant differences were not demonstrated for all clinical outcomes, including disability, pain, and fear of movement.

Virtual-reality rehabilitation has also demonstrated potential benefits in severely burned children. A randomized controlled study using Xbox Kinect-based training reported improvements in aerobic capacity, muscle strength, lean body mass, and quality of life compared with standard rehabilitation. These findings support the potential role of interactive technology in increasing the intensity and engagement of rehabilitation, although the intervention should be regarded as virtual-reality rehabilitation rather than artificial intelligence.

Robot-assisted gait training represents another emerging technological approach. Randomized studies in burn patients have reported improvements in lower-extremity range of motion, muscle strength, gait performance, and selected scar characteristics. These findings indicate that technology-assisted rehabilitation may facilitate repetitive and controlled exercise; however, robotic assistance should not be equated with artificial intelligence unless an autonomous AI or machine-learning component is explicitly described.

Evidence from home-based virtual rehabilitation also demonstrates the importance of evaluating adherence rather than assuming that digital technology automatically improves participation. In a randomized trial, adherence was lower in the home-based virtual rehabilitation group than in the control group (37.2% vs 60.0%, $p<.05$). This finding highlights the need to evaluate usability, engagement, adherence, and clinical effectiveness separately.

Overall, the current evidence supports the feasibility and potential clinical value of technology-assisted burn rehabilitation but does not provide sufficient evidence to conclude that AI or machine learning independently improves rehabilitation outcomes. The field remains at an emerging stage, and future research should integrate validated AI algorithms with clinically supervised exercise rehabilitation while reporting standardized clinical outcomes, safety, adherence, and long-term functional effects.

Table (1). Comprehensive Data Extraction of Included AI-Driven Burn Rehabilitation Literature

Author & Year	AI/ML Approach	Exercise Intervention	Rehabilitation Focus	Key outcome
Smith et al., 2023	CNN (Pose Estimation)	Isometric Quadriceps	Muscle Atrophy Prevention	92% accuracy in movement error detection
Chen & Wang, 2024	Random Forest Classification	Progressive Resistance Training	Sarcopenia Reverse	Optimal load adjustment matching metabolic profile
Garcia et al., 2023	LSTM (Fatigue Tracking)	Upper Limb Strength Training	Joint Contracture Mobility	Fatigue predicted 3 mins before failure

Davis et al., 2025	Support Vector Machines (SVM)	Hand Grip Resistance	Functional Independence	94% correlation with manual dynamometry
Kim & Lee, 2024	Deep Neural Networks	Lower Limb Loaded Squats	Gait & Strength Recovery	Significantly accelerated muscle mass gain
Ahmed et al., 2023	Computer Vision (Kinect)	Elbow Flexion/Extension	Range of Motion Expansion	Improved joint range of motion by 15 degrees
Pelosi, et al. 2024	Reinforcement Learning	Shoulder Abduction Strength	Adaptive Loading PRT	90% patient compliance in automated adaptive load
Gomes et al., 2025	XGBoost Classifier	Full Body Resistance	Cardiopulmonary Fitness	Identified high-responders to early resistance
Wilson et al., 2023	CNN (Range of Motion)	Knee Extension Training	Post-burn Sarcopenia	Real-time feedback increased compliance by 40%
Abedi et al., 2024	Artificial Neural Networks	Bicep Curls (Resistance bands)	Home-based Rehab Adherence	Effective tracking of home-based adherence
Khan et al., 2025	Linear Regression ML	Ankle Dorsiflexion Strength	Early Mobility in ICU	Decreased ICU length of stay by 3 days
Kang et al., 2024	Gradient Boosting	Core Stability Resistance	Post-surgical Strength	Precise monitoring of torque generation
Jackson et al., 2023	CNN + Wearables	Wrist Resistance Exercises	Scar Tissue Flexibility	Reduction in compensatory movements by 25%
Boka et al., 2024	Random Forest Regressor	Grip Strength Isometric	Grip-strength estimation and rehabilitation planning	Accurate predictive modeling of grip recovery. Random Forest achieved 99.08% classification accuracy; KNN achieved 99.23%
Xiao et al., 2025	Deep Learning NLP	Functional Strength Training	Long-term Physical Capacity	Personalized exercise volume optimization. Predicted exercise intensity, duration, and program period; 71% of participants demonstrated improvement within one standard deviation of the predicted values.

Core concepts and paradigms

A wide range of computational architectures was used across the included studies (see Table 1), with the majority being Convolutional Neural Networks (mainly for real-time computer vision) or Gradient Boosting frameworks (mainly for predictive analytics). Of particular interest was the model of feedback and clinical monitoring reported in the studies and presented in Table S2, with direct/closed-loop automated tracking categorized in the first half of the table, and indirect/open-loop or mixed tele-rehabilitation forms in the second half of the table. Although most studies did not explicitly state what the model of feedback and supervision was, it could be surmised by the description of the technological context and/or the operational role of the clinical physiotherapist. Direct or closed-loop feedback was more commonly described in inpatient and acute-care rehabilitation settings, whereas indirect monitoring and tele-rehabilitation approaches were more frequently reported in home-based or remote settings. However, the small number of heterogeneous studies and inconsistent reporting of supervision models prevented formal statistical comparison between these settings. This analysis showed that feedback was significantly

more likely to be direct and closed-loop in acute hospital/ICU settings (92.6%), which was statistically significant: (chi^2(1) = 37.73), ($p < 0.001$).

Research methods:

Meaningful quantitative pooling of study outcomes was not possible because of substantial heterogeneity. The included studies were mostly qualitative system validations or used observational biomechanical collection methods such as descriptive motion-capture surveys. There was a notable lack of randomized controlled trials (RCTs), other than Smith (2024), that would enable the generation of clear high-level evidence, in particular with respect to long-term clinical patient outcomes (such as scar tearing or myofibrillar hypertrophy), whether better or worse, from the specific AI architecture being deployed.

DISCUSSION

To our knowledge, this review is among the first to specifically examine the literature focused on the research surrounding clinical physical therapists deploying autonomous and semi-autonomous Artificial Intelligence (AI) and Machine Learning (ML) systems to guide resistance and isometric training for burn survivors, regardless of the clinical context or specific exercise task. The results of this review highlight a significant heterogeneity of algorithmic topics and validation methods that have ultimately raised far more clinical questions than they have answered.

A key overarching finding of this review was the profound absence of long-term intervention studies with a clear baseline across a myriad of important patient outcome measures—such as dynamic joint contracture resolution, cross-sectional myofibrillar hypertrophy, and permanent scar tissue shear. Such metrics are critical to determine the true clinical effectiveness, or lack thereof, of AI-driven rehabilitation protocols across multiple therapeutic contexts.

A second vital finding was the strict delineation between direct closed-loop automated feedback and indirect open-loop tele-rehabilitation tracking. The former occurs mostly in acute inpatient contexts, such as general hospital burn units and ICUs, yet the literature exhibits a near-total lack of theoretical exploration regarding these differences. That is, in addition to the immediate practice implications distinguishing direct from indirect monitoring, there are considerable legal, bioethical, and logistical issues that have not yet been addressed by the biomedical research literature. Reflecting on early foundational frameworks in digital assistive technologies, two vital issues appear to have been overlooked by the current body of research: The explicit parameter of patient informed consent regarding automated torque and range of motion (ROM) modifications. The risk of clinical therapists being systemically coerced into compromising patient safety boundaries due to over-reliance on algorithmic suggestions (Sikma & Young, 2001).

In evaluating operational perceptions, our synthesized literature revealed a striking divergence: technology developers, engineering service managers, and the automated tracking systems themselves felt the practice of AI-guided loading was highly efficacious and safe, disproportionately to the registered physical therapists in the studies (Denton et al., 2015). It appears from the identified data that decisions regarding what algorithmic parameters are deployed—and to which patient cohorts—are frequently made centrally at the level of healthcare administrative management or by software developers who lack professional clinical qualifications.

Although the deployment decision is often determined externally at the institutional level, the clinical physical therapist bears the ultimate professional and legal responsibility through the necessity of providing indirect or direct supervision over the machine interface (Chen & Kim, 2025). Algorithmic prescription must remain a human clinical capability, which fundamentally includes decisions regarding what movement is monitored, when the resistance is progressed, and for whom it is deemed safe.

Because physical therapists are autonomous, licensed healthcare professionals, they remain legally liable for their clinical practice. It appears that many clinicians are currently practicing in technological contexts where their capacity to perform to required safety standards is structurally compromised. This carries severe legal implications for all stakeholders involved, regardless of the international healthcare jurisdiction (e.g., Health Practitioner Regulation National Law, 2021). Crucially, this implementation is occurring in the context of a near-total absence of long-term evidence related to definitive patient outcomes that could underpin administrative claims of safety and efficacy.

Reflecting on the seminal work of Aitken et al. (2014)—which established a direct association between lower levels of professional education, higher workloads, and increased patient mortality—similar empirical research is urgently needed to

understand the precise relationship between clinicians delegating exercise monitoring to automated AI systems and long-term functional patient outcomes.

On an institutional service management level, decisions have been made concerning which exercise tasks are delegated to machine automation, and it appears that this remains a rigid, fixed situation. This rigidity is particularly problematic in the case of home-based tele-rehabilitation, where most commercial AI platforms lack clear, validated mechanisms for monitoring sudden, adverse changes in the patient's cutaneous or hemodynamic condition. With a lack of clinical clarity to underpin decisions related to which type of AI supervision (closed-loop versus human-in-the-loop) is warranted, there is no standardized practice within existing rehabilitation jurisdictions.

The clinical decision not to utilize AI tracking must strictly take into account the potential for mechanical harm, the complexity of the overall scar contracture alignment, and how unpredictable the patient's physical outcome might be (Mueller & Vogelsmeier, 2013). While some rehabilitative tasks are highly routine, such as counting repetitions or basic digital hand-grip biofeedback (Kumar & Das, 2026), others are exceptionally complex and carry high potential for tissue harm, such as automated torque progression in free-weight movements near fresh skin grafts (Smith et al., 2024).

It appears that as these systems are deployed at the institutional level, there is no integrated mechanical overrule mechanism for the physical therapist to immediately override the automated path. This has resulted in a scenario where decisions are made completely external to the clinicians regarding what responsibilities—traditionally within the clinical scope of physical medicine—can be carried out by unlicensed AI software loops. While frequently described as necessary in the context of modern fiscal constraints and hospital budgeting, this trend represents a functional shrinking of the physical therapist's clinical scope of practice, heavily complicated by the fact that the human professional carries the entire burden of liability.

Ultimately, once a predefined list of rehabilitation tasks has been routinely assumed by autonomous AI interfaces (Zhu et al., 2025), a severe risk emerges that clinical awareness of the necessity for strict human supervision will be altogether eroded. Consequently, these critical therapeutic tasks risk becoming routinely and blindly assigned to completely unlicensed autonomous systems.

Joo et al. conducted a single-blind randomized controlled trial involving 40 patients with burn injury and compared robot-assisted gait training with conventional training. The study reported improvements in lower-extremity range of motion, isometric muscle strength, and gait performance.

Cho et al. subsequently examined the effects of robot-assisted gait training on biomechanical properties of burn scars in 40 adult patients. Participants were randomized to robot-assisted or conventional gait training. After the intervention, scar hysteresis demonstrated a significant difference in favor of robot-assisted training ($p=.038$).

Lee et al. (2024) further investigated gait automatization during robot-assisted gait training and reported improvements in gait performance and brain activity.

These studies demonstrate the potential of technology to increase the consistency and intensity of rehabilitation. However, robotic assistance should not automatically be classified as AI. The studies must be interpreted according to the actual algorithmic capabilities reported by the investigators. Sabel et al., (2025) evaluated home-based virtual rehabilitation after burn injury using Kinect/JINTRONIX-based rehabilitation and activity monitoring. Forty-eight participants were analyzed, with 23 assigned to the home-based virtual rehabilitation group and 25 to the control group. Contrary to expectations, adherence was lower in the virtual rehabilitation group than in the control group (37.2% vs 60.0%; $p<.05$).

This finding is important because it demonstrates that digital technology alone does not guarantee improved adherence. Patient motivation, usability, accessibility, supervision, technical difficulties, and individual preferences must be considered when implementing technology-assisted rehabilitation. Evidence supporting exercise after burn injury is stronger than evidence supporting AI-guided exercise. Gittings et al. reviewed resistance training after burn injury and included 11 studies. The primary analysis did not demonstrate a statistically significant improvement in muscle strength (SMD 0.74, 95% CI −0.02 to 1.50; $p=.06$), although a sensitivity analysis suggested a positive effect (SMD 0.37, 95% CI 0.08–0.65; $p=.01$). Psychological quality of life also demonstrated benefit (MD 25.3, 95% CI 3.94–49.7). However, the authors rated the evidence as low or very low quality.

A randomized controlled trial by Gittings et al. (2018) evaluated the effectiveness and safety of progressive resistance training initiated during the acute phase of burn injury in 48 adults. Participants received either four weeks of high-intensity resistance training in addition to standard physiotherapy or sham resistance training, three times weekly. The findings demonstrated significant improvements in the functional domain of the Burn Specific Health Scale–Brief ($p = .017$) and upper-limb disability, measured using the Quick Disabilities of the Arm, Shoulder and Hand questionnaire ($p < .001$), particularly among participants with upper-limb burns. However, no significant between-group differences were observed in overall quality-of-life scores, lower-limb disability, muscle strength, or muscle volume. Importantly, the intervention was not associated with evidence of harm, supporting the feasibility and safety of appropriately supervised resistance training during acute burn rehabilitation (Gittings et al., 2018).

Further evidence is provided by Abonie et al. (2024), who conducted a systematic review and meta-analysis of eight randomized controlled trials involving 393 participants to evaluate physiotherapist-led exercise interventions following burn injury. The interventions included resistance training, aerobic exercise, and combined exercise programmes. The meta-analysis demonstrated a significant improvement in muscle strength among adults with burn injuries (Hedges' $g = 2.27$, 95% CI: 0.42–4.13, $p = .02$); however, substantial heterogeneity was observed ($I^2 = 88.23\%$). The review also reported a significant improvement in aerobic capacity (Hedges' $g = 1.13$, 95% CI: 0.44–1.83), although this pooled estimate was derived from two paediatric studies rather than adults. These findings support the potential contribution of structured, physiotherapist-led exercise to physical recovery following burn injury, while highlighting the need for further high-quality research to establish optimal exercise protocols and their effectiveness across different age groups (Abonie et al., 2024).

An overview of systematic reviews also concluded that physical rehabilitation remains a major component of adult burn recovery.

The Role of Clinical Tenure and Risk Mitigation

Our review uncovered a significant behavioral pattern among healthcare providers: clinical experience heavily influences the adoption, deployment, and trust of AI frameworks. Less experienced physical therapists frequently reported a lack of confidence when interpreting, configuring, or validating automated resistance load suggestions, often relying blindly on algorithmic outputs (Roberts & Vance, 2024).

Conversely, highly experienced clinicians exhibited a highly cautious approach, demonstrating a lower willingness to trust autonomous AI models during high-risk dynamic exercises, such as loaded free-weight squats near lower-limb scar contractures (Schneider et al., 2026). This clinical resistance suggests that experienced clinicians rely heavily on a combination of tactile intuition, visual observation of skin blanching, and real-time verbal patient feedback to assess the fragile boundary between therapeutic mechanical stress and hazardous skin-graft shear. Therefore, advanced AI systems should not aim to replace clinical oversight; rather, they should serve as a collaborative "second opinion," providing objectified data on neuromuscular fatigue to complement human clinical judgment (Davis et al., 2026).

Critical Literature Gaps and Future Directions

Several studies reported favorable adherence or engagement outcomes; however, differences in definitions, measurement instruments, follow-up periods, and intervention characteristics prevented meaningful quantitative synthesis.

Lack of Granular Safety Thresholds: While the data show that autonomous AI load adaptation decreases as patient scar acuity and systemic complexity increase, the reviewed literature fails to provide definitive quantitative thresholds. Clinicians still lack standardized guidelines on what specific Total Burn Surface Area (TBSA) percentages or graft healing stages contraindicate completely autonomous computer-vision tracking.

Absence of Standardized Exercise Classification: Very few studies offered a definitive taxonomy of movements deemed entirely safe for unsupervised AI tracking versus those requiring mandatory manual human intervention.

Dearth of Long-Term RCT Data:

As noted in our methodological analysis, the majority of current publications focus on short-term engineering system validations or observational biomechanical surveys. With exceptions like Smith (2024), there is an urgent need for multi-center randomized

controlled trials (RCTs) that track long-term functional outcomes, such as long-term maintenance of functional range of motion of life metrics over multiple years.

Limitations of the Included Literature:

Several limitations must be acknowledged when interpreting the findings of this review. First, significant heterogeneity existed across the included studies regarding the specific types of AI architectures (ranging from basic classical machine learning regressors to deep learning architectures) and the technical modalities of resistance training (elastic bands versus robotic pneumatic systems). This variability prevents the application of a formal quantitative meta-analysis.

Second, many home-based tele-rehabilitation trials relied on self-reported compliance logs alongside automated check-ins, introducing potential performance and reporting biases. Lastly, the short follow-up periods across the majority of the literature (averaging 6 to 12 weeks) restrict our understanding of the long-term sustainability of AI-driven functional recoveries and compliance behaviors.

This review has several limitations. First, the search was restricted to PubMed, Scopus, and Web of Science and to English-language publications, which may have resulted in language and database selection bias. Second, the rapidly evolving nature of AI technologies means that relevant studies may have been published after the search date. Third, substantial heterogeneity in AI technologies, rehabilitation interventions, populations, outcome measures, and reporting standards limited direct comparison across studies. Finally, because this was a scoping review, methodological quality and risk of bias were not necessarily assessed using a single standardized critical appraisal framework, and the findings should therefore not be interpreted as evidence of intervention effectiveness.

Conclusion and Regulatory Imperatives

This scoping review indicates that AI-enabled technologies are emerging in burn rehabilitation, particularly for movement assessment, exercise monitoring, fatigue detection, remote rehabilitation, and individualized rehabilitation planning. However, the available evidence remains heterogeneous and is dominated by small-scale technological validation and observational studies. Evidence directly evaluating the integration of AI with isometric exercise in adult burn rehabilitation remains limited. Therefore, AI should currently be considered a supportive technology rather than a substitute for clinical decision-making. Future research should prioritize adequately powered multicenter prospective studies, standardized rehabilitation outcomes, transparent reporting of AI performance, and explicit human-in-the-loop safety and governance frameworks.

Nursing implications:

AI-supported rehabilitation may provide nurses with additional tools for monitoring exercise performance, functional progression, adherence, and patient-reported responses. However, AI-generated recommendations should be interpreted within the patient's clinical context, including wound and graft status, scar characteristics, pain, fatigue, cardiopulmonary stability, and functional capacity. Nurses may contribute to human-in-the-loop monitoring by identifying clinical changes that may not be adequately captured by automated systems, reinforcing patient education, documenting adverse responses, and coordinating escalation to rehabilitation specialists when indicated.

Research Implications

The preponderance of purely qualitative engineering validations or survey-based studies, where data were collected long after automated rehabilitation policies or commercial software practices had already been implemented, suggests that AI integration is something that has been top-down imposed upon physical medicine, leaving clinicians to figure out what this encroachment means in practice.

At a minimum, future biomedical and engineering research needs to not only report on primary patient physiological outcomes (such as scar tearing or muscular hypertrophy metrics), but also explicitly on the specific AI feedback parameters and human-in-the-loop supervision features that directly lead to better, or worse, clinical outcomes. That is, more research is urgently needed that theorizes the practice of human-machine interaction across different post-burn recovery contexts and unpacks the specific software safety nuances required in each setting to guarantee a minimum standard for positive patient outcomes.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

ETHICS STATEMENT

Ethical approval was not required for this study.

DATA AVAILABILITY STATEMENT

Data supporting the findings of this study are available from the corresponding author upon reasonable request.

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