Application of Artificial Intelligence and Internet of Things in Rehabilitation and Health Recovery

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Abstract*. Both Artificial Intelligence (AI) and the Internet of Things (IoT) optimize different aspects of human life. This is also the case with human health. This research focuses on the application of AI and IoT in rehabilitation and health recovery, with a particular emphasis on physical recovery and kinesiotherapy. The primary goals of this literature review are twofold. First, to analyse the literature related to the application of AI and IoT in rehabilitation and health recovery, focusing on the addressed health issues, applied AI solutions, IoT and robotics solutions, technology readiness levels of AIoT systems, and publications and their authors (years of publishing, journals, conferences, countries of origin). Second, to analyse papers related to physical therapy and kinesiotherapy AI and IoT to determine how those they are integrated. The literature review was implemented using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach. In total, 77 papers were analysed. They are mainly journal papers. The number of publications has increased over the years. When analysing the AIoT solutions related to physical therapy, most systems are in prototype or pilot stages and show promising results towards better recovery and quality of life for patients.*

Keywords: AI, IoT, sensors, health, physical rehabilitation

1 Introduction

This paper has been prepared under the project "Research and Development of an Integrated Artificial Intelligence – Internet of Things (AIoT) Solution for the Personalization of Physical Therapy and Kinesitherapy – AIoT4Therapy", which aims to develop a comprehensive AIoT solution for physical therapy and kinesiotherapy, integrating innovative sensor systems, multi-criteria decision-making, advanced AI algorithms to optimize the therapeutic process, and specially trained language models to advise patients and experts. The solution will be available to end users in the form of an intuitive, easy-to-use digital tool. The goal of the project is to enable more personalized therapeutic procedures, ensure continuous system improvement based on patient feedback, and provide a platform for more effective education of experts and patients, particularly through large language models (LLMs). When implemented, the solution aims to significantly enhance the effectiveness of existing therapeutic procedures, reduce the incidence of musculoskeletal diseases through everyday use, and improve the overall quality of life for patients.

The goal of this paper is to analyse the current state of the application of AI and IoT in health recovery and rehabilitation. The research is a literature review, conducted using a PRISMA approach (Page et al., 2021) on the scientific articles databases, Web of Science (WoS) and Scopus. The analyses were focused on identification of (1) health recovery issues that are analysed using AI and IoT, (2) AI methods, approaches and solutions that were used to deal with the rehabilitation and health recovery issues, (3) IoT devices that were used to deal with the rehabilitation and health recovery issues, (4) levels of application of AIoT healthcare solutions for rehabilitation and recovery issues, and (5) descriptions of AIoT solutions primarily related to physical therapy;and the determination of (1) the distribution of the number of papers considering the year of publication, (2) the distribution of the number of papers per countries (based on authors affiliations' countries), (3) the number of papers considering the publications and the types of publications.

The paper is organised as follows: Section 2 describes the potential of AI and IoT devices in healthcare. Section 3 presents the research methodology. Section 4 presents the results of the research. Section 5 concludes the paper.

2 AI and IoT in Healthcare

The following two paragraphs present claims found in the existing literature and do not reflect the original theses of this paper. Artificial Intelligence (AI) and the Internet of Things (IoT) are transformative technologies that are reshaping industries worldwide. Below is an explanation of these technologies and their applications across various sectors. AI refers to the simulation of human intelligence in machines that can perform tasks such as learning, reasoning, problem-solving, and decision-making. It encompasses technologies like machine learning (ML), natural language processing (NLP), and computer vision, which allow systems to analyse data, recognize patterns, and make predictions or decisions. IoT involves a network of interconnected devices that collect, share, and analyse data through the internet. These devices include sensors, wearables, and smart appliances that enable real-time monitoring, automation, and data-driven decision-making.

AI and IoT technologies are integrated across diverse sectors, including healthcare, smart cities, manufacturing, and agriculture, utilizing sensor data and machine learning algorithms for various applications. The combination of AI and IoT enhances their individual capabilities: IoT provides massive amounts of real-time data from connected devices. AI processes this data to generate actionable insights, enabling smarter automation, predictive analytics, and improved decision-making. For example, in healthcare, IoT devices collect patient data while AI analyses it for early diagnosis. In manufacturing, IoT sensors monitor equipment while AI predicts maintenance needs. Both technologies are driving innovation across industries by improving efficiency, reducing costs, and enhancing user experiences.

Some studies report applications in healthcare, smart cities, industrial manufacturing, robotics, and automation (Ma et al., 2019). In healthcare, Mahalakshmi (2019) and Oniani et al. (2020) describe systems that use machine learning, support vector machines, k-nearest neighbours, and other algorithms in combination with medical sensors and Internet of Medical Things devices (Oniani et al., 2021; S Mahalakshmi, 2019). These studies detail diagnostic tools, patient data analysis, predictive disease management, and robotic surgery enhancements. Other studies illustrate urban and industrial uses. Ma et al. (2019) and Mali (2019) note smart public services and intelligent manufacturing that rely on IoT sensor data and AI analytics for tasks such as traffic monitoring and process optimization. G Tzafestas (2018) discusses the integration of AI with IoT to improve robotics, automation, and industrial operations. Additional application areas include smart homes, transportation, agriculture, and marketing, each mentioned in one study (G Tzafestas, 2018; Mali, 2019).

Innovation in medical treatment relies on formal R&D processes, clinical practice feedback, and enabling factors like public-private partnerships and regulatory frameworks (Kaitin et al., 2011; Kanavos et al., 2010). Formal research and development processes support innovation in medical treatment (Cheng et al., 1996; Garber et al., 2014; Lo et al., 2022). Studies document a shift from disorganized beginnings toward refined, targeted approaches in pharmaceutical and anticancer drug development (Liu et al., 2017). For example, analyses reveal an increased focus on priority products even as overall approval rates decline, while historical reviews note a move toward targeted and immune-related therapies (Mahoney, 2011).

Clinical practice feedback loops also drive innovation. Investigations into medical device development and mechanism-based pain diagnosis show that input from end users helps refine and direct product design (Woolf et al., 2001). Technology transfer through product development partnerships facilitates the adoption of non-medical technologies for medical use. Moreover, collaborative public–private partnerships, evolving regulatory frameworks that both constrain and hasten approval, and robust funding structures emerge as key enablers in shaping a dynamic, non-linear innovation process (Kanavos et al., 2010).

Many studies report that integrating AI and IoT (or IMU (Inertial Measurement Unit)) in healthcare can improve remote monitoring, diagnostics, and overall clinical care. Chintala (2024) describes a remote patient monitoring system in which IoT devices combined with AI algorithms yield better clinical outcomes, lower costs, and higher patient satisfaction (Chintala, 2024). Dwivedi et al. (2021) and Ejiyi et al. (2023) detail layered and edge-based Internet of Medical Things (IoMT) systems that support telehealth, self-monitoring, rehabilitation, and chronic disease management while enhancing patient outcomes and cost-effectiveness (Dwivedi et al., 2022; Ejiyi et al., 2023). Ghode et al. (2024) presents a healthcare analytics framework that increases diagnostic accuracy and enables personalized care through real-time data analysis. One review of IoT applications outlines use cases in patient monitoring and supply chain management without detailing specific outcomes (Akoh Atadoga et al., 2024). Common themes include real-time insights for early diagnosis and rapid intervention, along with challenges in data privacy, interoperability, and system integration that may affect implementation (Chintala, 2024; Ghode et al., 2024).

The most promising AI and IoT technologies in healthcare today are AI-powered diagnostics, robotic surgery, personalized medicine, virtual health assistants, drug discovery, internet of medical things, ambient clinical intelligence, precision imaging and predictive analytics for emergency care.

3 Methodology of the Research

In this research, we defined several research questions (RQ) to achieve the research goals:

RQ1. Which rehabilitation and health recovery issues are analysed using AI and IoT?

RQ2. Which AI solutions, methods and approaches are used to deal with rehabilitation and health recovery issues?

RQ3. Which IoT devices are used to deal with rehabilitation and health recovery issues?
RQ4. What are the levels of application (or technology readiness levels, TRLs) of IoT-AI-healthcare solutions for rehabilitation and health recovery reported in the literature?
RQ5. What is the distribution of papers considering the year of publication?
RQ6. What is the geographical distribution of the authors of the papers related to analysing rehabilitation and health recovery issues using AI and IoT?
RQ7. What is the type of publication where the papers are published (conferences and/or journals)?
RQ8. What are the strengths and weaknesses of AIoT solutions created for optimize physical therapy and kinesiotherapy?

Literature review using PRISMA approach was applied to answer the previous research questions. The PRISMA approach is a widely recognized framework designed to enhance the transparency, quality, and reproducibility of systematic reviews and meta-analyses. It provides a structured methodology for reporting the process and findings of such reviews.

The databases that were searched in are Web of Science (WoS) and Scopus.

The keywords that were searched are:

- AI IOT Therapy,
- AI IOT Kinesiotherapy,
- AI IOT Physical therapy
- AI IOT Rehabilitation,
- AI IOT Recovery Health,
- AI IMU Therapy,
- AI IMU Kinesiotherapy,
- AI IMU Physical therapy,
- AI IMU Rehabilitation.

Inside each item in the list, there is an operator AND, and among all items in the list, there is an operator OR. Fig. 1 presents the flow diagram of PRISMA steps implemented in the research considering the research questions.

After the initial search, there were 111 records in WoS, and 178 records in Scopus. Many of the records were found in both databases (the number of duplicated records was 105). After duplicates removal, there were 184 records. In a subsequent step, an open-access filter was applied, and 79 records remained for analysis. During the access to the full papers, two papers were not found, so 77 papers remained for the analysis. Those 77 papers cover all medical categories since rehabilitation is associated with different medical states.

Furthermore, it was decided that RQs 1 to 7 will be analysed across the entire set of 77 papers to describe the state of AIoT application in all healthcare categories, and RQ 8 will be analysed in the sample that remains after applying the filter health category = physical disease, 12 papers since the AIoT4Therapy project is related to physical therapy.

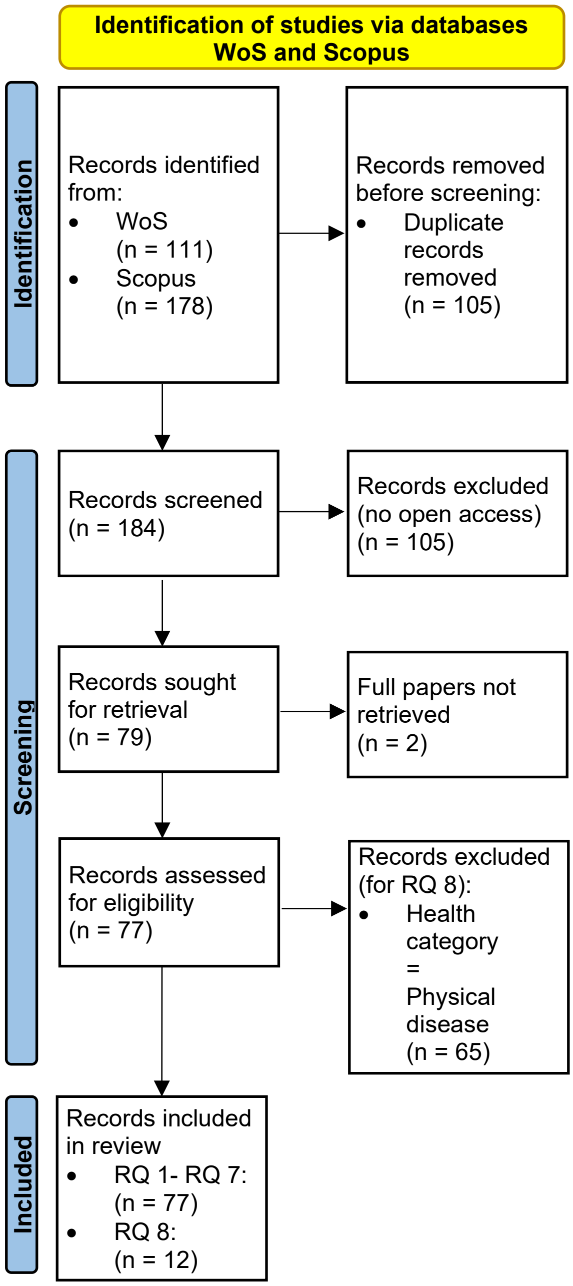

Figure 1. PRISMA flow diagram

4 Results

4.1 AI and IoT in rehabilitation and health recovery

The distribution of the number of papers respecting the health category is presented in Table 1. The highest number of papers discuss the general application of AI and IoT in healthcare. Considering concrete diseases, the highest number of papers are related to physical disease (12), followed by stroke rehabilitation (7), cancer (6) and mental health (6). The following tables are primarily sorted alphabetically (Tables 1–4 and 6). Table 5 is sorted chronologically by year.

Table 1. Number of papers per health category (RQ1)

Health category	Number of records
Cancer	6
Chronic disease	5
Healthcare in general	30
Heart disease	5
Mental health	6
Not healthcare	*3*
Ophthalmology	1
Physical disease	12
Stroke rehabilitation	7
Traumatic brain injury	2
Grand total	77

Table 2. Number of papers per AI solutions, methods and approaches (RQ2)

AI solutions	Number of records
AI (general)	70
Artificial Neural Network	8
Augmentation methods	14
Big Data Analytics	45
Convolutional Neural Network	14
Deep Learning	35
Edge computing	16
Machine Learning	55
Natural Language Processing	3
Simulations	23
Simultaneous Localization and Mapping	1

The distribution of the number of papers with respect to AI solutions, methods and approaches that were used or discussed in the context of rehabilitation and health recovery is presented in Table 2. As can be seen in the table, not all AI solutions, methods, and approaches are at the same level. Convolutional Neural Networks belong to the category of Artificial Neural Networks, which are a subset of deep learning. Furthermore, deep learning is a subset of machine learning, and all methods share a common umbrella of AI.

The distribution of IoT devices which are used to deal with rehabilitation and health recovery issues is presented in Table 3. The most commonly used IoT devices are sensors (some papers specify the type of sensors, so we identified GPS sensors, vital signs sensors, optical motion sensors, among others), followed by wearables and Wi-Fi devices.

Furthermore, we analysed all papers and categorised them based on the level of development of AIoT devices. Even though there are commonly accepted technological readiness levels (TRLs), it was hard to distinguish between levels of some AIoT solutions in papers, so we introduced a simpler scale for this purpose. As can be seen in Table 4, we differ (1) papers that are related to the review of trends (that theoretically discuss the possibilities of AI and IoT application in rehabilitation and health recovery, without proposing any concrete solution; some of those papers were literature reviews), (2) papers that present the ideas how certain AIoT can be introduced (ex. Ergen and Belcastro (2019) presented the concept of AIoT integration in medicine), (3) papers that present the designs of AIoT systems (ex. Gomez-Valiente et al. (2023) presented an IoT architecture to support a smart IoT that focuses on addressing the challenges of scheduling, resource allocation, and state management of Smart IoT systems), (4) the papers that describe the prototypes of the systems and (5) papers that present the results of the application of prototypes in the real environment (ex. Moghbelan et al. (2024) proposed a smart motor rehabilitation system which leverages wearable sensors to monitor patients' vital signs and edge computing to detect and estimate motor routines). The highest number of papers is related to the category of the review of trends, followed by the prototype applications and designs of the AIoT systems. Some examples are described in Section 4.2.

Table 3. Number of papers per IoT devices (RQ3)

IoT devices	Number of records
AR/VR	9
Bed mat	2
Cameras (2D/3D)	22
Doppler/Ultrasound	2
Floor sensors	3
GPS Sensors	2
IMU	12
Optical motion sensor (Kinect)	2
Robots	11
Sensors	63
Triboelectric nanogenerator (TENG) sensors	2
Vital signs sensor	28
Wearables	40
Wi-Fi-enabled Microscopic Device	35

Table 4. Number of papers per level of AIoT system development (RQ4)

Level of AIoT system development	Number of records
AIoT idea	2
AIoT system design	11
Prototype description	1
The application of prototypes in a real environment	29
The review of trends (including literature reviews)	34
Grand total	77

Considering the year of publication and the type of publication, the results are presented in Table 5. We can see that the first ideas of applying AI and IoT for rehabilitation and health recovery were documented in 2019, and that the number of papers increases each year.

The papers were mainly published in journals, in more than 50 journals. The most popular journals are Applied Sciences (MDPI), Sensors (MDPI) and IEEE Access (IEEE), Computers (MDPI), Healthcare (MDPI), IEEE Internet of Things Journal (IEEE) and Information (MDPI). Other journals published only one paper.

Table 5. Number of papers per year and publication type (RQ5)

Year	Journal	Conference	Total
2019	2		2
2020	3		3
2021	9		9
2022	11	1	12
2023	19		19
2024	27	2	29
2025	3		3
Grand total	74	3	77

Table 6. Number of papers per country (RQ6)

Country	Number of papers	Country	Number of papers
Australia	9	Norway	2
Bangladesh	3	Pakistan	4
Belgium	1	Poland	1
Brazil	2	Portugal	1
Canada	6	Saudi Arabia	10
China	15	Serbia	1
Ecuador	1	Singapore	3
Egypt	2	South Korea	6
Germany	1	Spain	5
India	16	Sweden	1
Iran	4	Taiwan	6
Israel	1	Thailand	1
Italy	6	Tunisia	1
Japan	1	Turkey	2
Lithuania	1	United Arab Emirates	1
Malaysia	3	United Kingdom	4
Nepal	1	United States of America	10
Nigeria	1		

Table 6 presents the distribution of papers per country, where the authors of papers come from. The highest number of papers is authored by Chinese and also Indian authors, followed by authors from Saudi Arabia, the United States of America and Australia. Authors from Asia dominate in the field.

4.2 AIoT-based solutions for physical therapy

In this subsection, we present descriptions of AIoT papers that belong to the health category of physical disease (RQ8). The last step from the PRISMA methodology finished with 12 papers, and they are analysed further.

Qayyum et al. applied machine learning to evaluate a herbal remedy (linseed, psyllium, and honey pessary) versus standard antibiotics for pelvic inflammatory disease. A clinical trial showed the herbal treatment is a safe and effective alternative, with the treatment group achieving over 70% improvement in key clinical outcomes. Patients on the herbal therapy had slightly greater reductions in symptoms (e.g. abnormal discharge reduced by 87% vs. 78% in controls). ML classifiers (decision tree, random forest, etc.) could only moderately distinguish the two groups (~53–62% accuracy), indicating comparable efficacy. High patient compliance (~98%) was observed in both groups, supporting the herbal AIoT approach as a viable therapy option (Qayyum et al., 2023).

Zhang et al. developed wearable triboelectric nanogenerator sensors for gait and waist motion tracking in lower-limb rehabilitation. Four textile-based sensors on a belt capture waist movement for real-time robot control and AR/VR exercises, while two insole sensors monitor gait. Using an ANN, the system achieved 98.4% accuracy in identifying individuals from gait signals (tested on five users). The integrated system, including a rehab robot and immersive game, performed well in user recognition and motion monitoring, enabling gaming-aided training and demonstrating potential for IoT-based smart rehabilitation. This low-cost, energy-efficient AIoT solution is presented as a prototype for future smart healthcare (Zhang et al., 2022).

Rahman et al. explored upper-limb rehabilitation by classifying elbow joint angles using surface EMG signals. They recorded biceps muscle activity at five fixed elbow angles and extracted time-domain features. A k-NN classifier achieved high accuracy, especially with k-fold cross-validation (mean ~89.7% vs. 82.5% with leave-one-out). This result demonstrates that a wearable EMG sensor can discern elbow flexion angles with nearly 90% accuracy, which could aid in developing advanced assistive devices and remote monitoring of rehabilitation exercises (Rahman et al., 2021).

Lin and Wai proposed an AIoT-based fall evaluation and prevention program for community-dwelling older adults. Their system uses gait and balance gesture data (based on sarcopenia criteria) with adaptive training courses reviewed bi-weekly by experts. In a 3-month field intervention, participants significantly improved their gait speed (mean increase of ~30% in males and 34% in females). The study demonstrates that AI-guided rehabilitation can improve mobility in sub-healthy seniors, and it provided insights into how gait and gesture patterns relate to stability, enabling targeted interventions to minimize fall risk. This pilot highlights effective health promotion through AIoT in long-term care (Lin et al., 2021).

Nadian-Ghomsheh et al. introduced a hierarchical IoT architecture for remote hand rehabilitation that emphasizes privacy. The system uses camera-based range-of-motion (ROM) tracking for hand/wrist exercises, with edge processing (including federated learning for skin detection) to avoid sending sensitive images to the cloud. A machine-learning module immediately assesses patient exercises and extracts ROM data to track progress. In tests, the vision-based method (using simple colored markers and standard RGB cameras) measured wrist/finger ROM with high accuracy, comparable to a goniometer and outperforming a depth camera (Leap Motion) in precision. The solution achieves real-time, accurate exercise assessment in a privacy-preserving manner, demonstrating an effective tele-rehabilitation tool that addresses data protection concerns in AIoT healthcare (Nadian-Ghomsheh et al., 2021).

Moghbelan et al. proposed the I-TROPHYTS framework, integrating wearable IoT sensors, edge computing, and a humanoid robot for group motor rehabilitation exercises. The system monitors patients' vitals and movements (via IMUs on the wrist and elbow) and uses an ontology-driven approach to model therapy sessions. The humanoid robot acts as an adaptive physiotherapist, demonstrating and adjusting exercises in real-time based on patient status. A pilot with volunteers doing shoulder exercises achieved nearly 100% accuracy in automatically distinguishing different movements (shoulder abduction vs. flexion) using machine learning on the IMU data. These results validate the framework's ability to automatically detect exercise types with high accuracy, supporting personalized and sustainable rehabilitation through AIoT and robotics (Moghbelan et al., 2024).

Shefa et al. designed a smart ankle–foot orthosis (AFO) system for gait rehabilitation, combining IoT sensors and deep learning. The AFO device is outfitted with a surface EMG sensor (to read muscle activity) and an IMU (to track leg motion), streaming data via fog computing for analysis. Multiple AI models were tested to classify walking patterns; a Transformer model performed best, achieving 98.97% accuracy in recognizing gait phases (normal vs. aberrant). This high accuracy enables the system to precisely detect abnormal gait events and quantify improvements in walking patterns. The platform can then provide personalized recommendations on AFO usage (duration and intensity) tailored to the patient's recovery needs, with clinicians reviewing the data for validation. This AIoT approach shows effectiveness in optimizing gait training and supporting data-driven orthotic therapy (Shefa et al., 2024).

Yao et al. (2023) developed a multifunctional smart heating pad to aid rehabilitation and pain relief, focusing on usability for older adults. The device uses an IoMT architecture with an onboard microcontroller and Bluetooth, employing fuzzy logic at the edge to regulate temperature without cloud support. The team designed a custom temperature sensor circuit with high stability (achieving ±0.3 °C accuracy in the therapeutic range). Experimental results confirmed the system's feasibility: the IoT controller self-calibrates and maintains target temperature ranges for different therapy modes using fuzzy rules, and achieves stability on par with expensive industrial controllers while using low-cost components. The heating pad's multiple modes (for various body areas or conditions) and auto-calibration make it user-friendly for seniors, illustrating how AIoT edge computing can improve traditional therapeutic devices (Yao et al., 2022).

Petrovic et al. conducted an experimental study using IoT force and EMG sensors to assess the safety of repetitive pushing/pulling tasks (simulating industrial cart handling) in relation to workers' pain and mental stress. Two 3-axis force sensors (on cart handles) and six EMG electrodes (on major upper-body muscles) collected data from participants with and without musculoskeletal pain or high psychological stress. Analysis revealed clear differences: subjects with pain or elevated stress showed significantly higher exertion (force integral) and muscle activation (EMG mean values) during the task. The study is the first to jointly evaluate how pain, spinal mobility, and psychological state affect task execution, concluding that these factors significantly degrade task performance and likely raise injury risk. The authors suggest using these AIoT measurements for personalized risk assessment in the future, with plans to incorporate computer vision (posture tracking) and EEG-based cognitive load monitoring to improve the system (Petrovic et al., 2022).

Alsareii et al. demonstrated a pilot IoT framework for remotely monitoring post-surgical patients using machine learning and ultra-reliable communication. Their system optimizes IoT network settings to ensure low-latency, stable transmission of patients' vital signs and activity data, even for critical patients. In simulations, the proposed network achieved reduced delay and packet loss compared to standard low-latency networks, improving reliability of data delivery. Additionally, a gradient-boosting regression model was employed to predict patient vital signs locally. This AI model could accurately forecast both slow-changing and fast-changing vital signals, effectively acting as a "virtual sensor" to fill in data gaps during connectivity outages. The results indicate that AIoT can enable robust, continuous monitoring for recovery patients, ensuring timely detection of issues despite network disruptions. This pilot underscores the feasibility of combining optimized IoT communications with ML prediction to enhance post-operative care (Alsareii et al., 2022).

Al-Hababi et al. introduced a novel non-contact sensing testbed using wireless signals and AI to monitor rehabilitation exercises in post-surgery patients. Instead of wearables or cameras, the system employs a Universal Software Radio Peripheral (USRP) to capture WiFi channel state information (WCSI) as patients perform prescribed movements (e.g. a weight-lifting exercise). Machine learning (a fine-tuned k-NN classifier) analyses the wireless signal perturbations to classify whether the patient executed the movement correctly or incorrectly. The experimental setup (with data from spinal surgery patients lifting weight) achieved 99.6% classification accuracy in distinguishing correct vs. incorrect form. This highlights an innovative AIoT approach for physical therapy: leveraging ubiquitous wireless signals to passively monitor exercise compliance and technique. Such a system could remind patients to maintain proper form (reducing complications) without requiring cameras or attached sensors, though it remains at a prototype stage (Al-Hababi et al., 2020).

Hasan et al. conducted a scoping review of digital health interventions for musculoskeletal pain, focusing on systems that use AI, IoT, and ML to improve outcomes. The reviewed evidence indicates that AIoT-driven solutions (including smart exercise coaching apps, remote monitoring tools, and even brain-computer interfaces) can help reduce pain and improve functional impairment in chronic conditions like low back pain and osteoarthritis. A key benefit is improved adherence to prescribed exercise therapy: intelligent systems provide reminders, feedback, and motivation, helping patients perform rehab exercises regularly to relieve pain. Overall, the review found that such digital therapies have received largely favourable feedback from patients and can offer convenient, cost-effective care. However, some users reported dissatisfaction, and current computer-aided rehab systems still “lack flexibility and robustness” in fully tailoring to individual needs. The authors conclude that AIoT-based interventions show substantial promise in musculoskeletal rehabilitation, but wider adoption and more research are needed to generalise their use and maximise patient outcomes (Hasan et al., 2023).

The analysis of 12 studies related to AIoT in rehabilitation is upgraded with the analysis of the advantages and limitations presented in Table 7.

The integration of Artificial Intelligence (AI) and the Internet of Things (IoT) into physical rehabilitation has marked a significant shift toward more personalized, data-driven, and accessible healthcare solutions. Current AIoT applications range from wearable sensors and smart orthoses to non-contact monitoring systems and robotic assistants, offering real-time feedback, precise motion analysis, and remote supervision. These technologies have demonstrated promising results in enhancing therapy adherence, optimizing treatment outcomes, and supporting clinicians with objective performance data. Emerging trends include privacy-preserving

Table 7. Analysis of advantages and limitations

Study	Advantages	Limitations
Qayyum et al. (2023)	Clinically effective herbal alternative; high patient adherence; non-antibiotic option	Limited diagnostic classification power of Machine Learning (~62% accuracy); Pelvic Inflammatory Disease-specific study
Zhang et al. (2022)	High identification accuracy (98.4%); immersive rehab gaming; low-power wearable design	Only tested on 5 users; limited generalizability
Rahman et al. (2021)	High angle classification accuracy (~90%)	Only elbow joint tested; simple movement classification
Lin et al. (2021)	Improved gait metrics in elderly; low-cost fall risk monitoring; real-world intervention study	Short duration (3 months); limited to Taiwan community setting
Nadian-Ghomsheh et al. (2021)	Privacy-preserving architecture; high Range of Motion measurement precision; real-time edge processing	Marker setup required; Range of Motion-focused, no muscle feedback
Moghbelan et al. (2024)	High exercise recognition accuracy (~100%); adaptive group therapy via robot; ontology-based logic	Prototype stage; complex hardware integration
Shefa et al. (2024)	High gait phase accuracy (~99%), personalized feedback	Focus on gait; needs Ankle–Foot Orthosis hardware
Yao et al. (2022)	Accurate self-calibrating temperature control; low-cost; older adult friendly	Passive therapy only; limited to heating/pain relief
Petrovic et al. (2022)	Multimodal data fusion (pain, stress, spinal mobility); real work-task safety assessment	Assessment-focused; no rehabilitation feedback or therapy
Alsareii et al. (2022)	High resilience in patient monitoring; local Artificial Intelligence prediction during outages	Simulation results only; no clinical deployment
Al-Hababi et al. (2020)	Very high form classification accuracy (99.6%); no wearables or cameras needed	Specific use-case; early prototype, small study size
Hasan et al. (2023)	Broad evidence, improved adherence, cost-effective	Limited robustness/flexibility in current systems

architectures, edge computing, and immersive rehabilitation environments using augmented or virtual reality. Despite the promising advances, many solutions remain in prototype or pilot stages, with limited clinical validation and scalability. Looking forward, the continued development of robust, interoperable, and user-centred AIoT systems is expected to expand access to rehabilitation services, especially for ageing populations and remote communities, while promoting a shift toward preventive and personalised care models.

5 Conclusion

The number of studies dealing with the application of AIoT for rehabilitation purposes increases from year to year. They are related to several health categories, mostly to healthcare in general and physical. The most active authors come from Asia (India and China). The papers are published in a large number of journals. Most of the papers present the developed prototypes and their applications, which often correspond to the TLR 4 and higher.

AIoT-based systems in physical therapy and kinesiotherapy demonstrate significant potential for improving rehabilitation through continuous monitoring, personalized feedback, and intelligent intervention. Studies show high accuracy in detecting patient states and positive health outcomes, including enhanced mobility, pain reduction, and better adherence to therapy. AI-driven personalization ensures treatments adapt to individual needs, while advanced sensing technologies enable real-time progress tracking.

Despite promising results, challenges remain, such as limited large-scale validation, data privacy concerns, and integration into clinical workflows. Many systems are still in prototype stages, requiring further refinement for usability, reliability, and wide-spread adoption. Future research should focus on long-term clinical trials and robust security measures to enhance trust and effectiveness.

With continued advancements, AIoT solutions are poised to transform rehabilitation by making therapy more accessible, data-driven, and effective, ultimately improving patient recovery and quality of life.

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