Traumatology and Orthopaedics of Kazakhstan
ISSN - e2789-9640

*Review article*

# AI-Driven Smart Wearable Systems for Personalized Rehabilitation Monitoring

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Received: 24 May 2025
Revised: 30 June 2025
Accepted: 27 July 2025
Published: 31 August 2025

**Citation:** Roza Beisembekova, Tanzhuldyz Aidarova, Assiya Boltaboeva, Baglan Imanbek, Kassymbek Ozhikenov, Nurgul Karymsakova. AI-Driven Smart Wearable Systems for Personalized Rehabilitation Monitoring. Trauma & Ortho Kaz, 2025, 76 (4), jto010 https://doi.org/10.52889/1684-9280-2025-76-4-jto010



## Abstract

The growing demand for personalized and effective rehabilitation strategies has driven the development of AI-driven smart wearable systems. These systems provide real-time health monitoring, prediction, and adaptive feedback, which helps to improve clinical outcomes in neuro-musculoskeletal and postoperative rehabilitation. This scoping review analyzes 14 peer-reviewed articles published between 2018 and 2025, comprising clinical trials, cohort studies, and engineering applications. The selected studies were identified through structured searches in IEEE, MDPI, and other scholarly databases, based on relevance to AI-enhanced wearable rehabilitation devices. Commonly used AI algorithms include support vector machines (SVM), convolutional neural networks (CNN), and reinforcement learning (RL), enabling functions such as gait analysis, joint movement recognition, muscle activation tracking, and postural control. In addition, integration with IoT sensor networks, cloud-based platforms, and telemedicine interfaces was widely reported. The review finds that AI-enabled wearables significantly improve patient adherence, monitoring accuracy, and personalized therapy delivery. Nonetheless, challenges remain in data security, sensor calibration, interoperability, and long-term user retention. These results confirm that smart wearables play an important role in supporting personalized, data-driven rehabilitation.

**Keywords:** AI wearables, personalized rehabilitation, remote monitoring, gait analysis, machine learning, telemedicine, smart health.

## 1. Introduction

In recent years, the continuous shift towards personalized and data-driven healthcare has accelerated the adoption of intelligent digital technologies within rehabilitation medicine. Among these, wearable systems integrated with artificial intelligence (AI) have become a promising tool to address the increasing demand for precise, patient-specific monitoring and adaptive therapeutic guidance. By capturing real-time physiological and biomechanical signals, smart wearables offer clinicians and patients the opportunity to track recovery progress remotely and adjust treatment regimens dynamically.

Modern AI-driven wearable systems typically use sensors like inertial measurement units (IMU), surface electromyography (EMG) electrodes, ECG, etc. and wireless data transmission modules. Such multi-sensor architectures allow the continuous recording of complex body movement patterns, muscle activation, and vital signs. The author Deng et al. (2023) presented a comprehensive design that integrates IMUs, ECG, EMG, oxygen saturation ($SpO_2$), and body temperature sensors within a wireless, edge-computing-enabled module to ensure uninterrupted home-based health monitoring. Their architecture demonstrates how different biosignals can be fused and pre-processed locally before cloud transmission, allowing real-time feedback with minimal latency and reduced data overload for remote medical supervision [1].

The collected multimodal data streams are typically processed by advanced machine learning algorithms, including convolutional neural networks (CNNs), support vector machines (SVMs), and reinforcement learning (RL) models. These algorithms are capable of recognizing deviations in joint kinematics, classifying rehabilitation phases, and providing timely predictive feedback to personalize exercise loads. A concrete example is the study by O'Brien et al. (2022), who demonstrated that IMU sensors worn on the waist and ankles, when combined with a balanced random forest model, can accurately predict the walking function of stroke patients after inpatient rehabilitation. In their cohort of over 30 patients, the proposed wearable-based AI model achieved an area under the receiver operating characteristic curve (AUROC) of 0.988, outperforming standard clinical assessments which reached only 0.905. This shows that wearable AI systems can complement traditional evaluation methods by delivering higher prediction precision for post-stroke ambulatory outcomes [2].

Beyond individual algorithms, the integration of AI-powered wearables into wider IoT and cloud-based ecosystems expands the reach of rehabilitation monitoring and supports tele-rehabilitation services. Shajari et al. (2023) emphasized in their comprehensive review that AI-based wearable sensors are playing an increasingly central role in digital health technologies, including chronic disease management, continuous physiological monitoring, and decentralized patient supervision. Their review also notes persistent barriers, such as sensor calibration drift, interoperability with electronic health record (EHR) systems, and the lack of standardized frameworks to validate AI outputs under diverse clinical conditions [3].

These challenges indicate that large-scale trials and clear regulations are needed such systems can be deployed safely and reliably on a population level [3]. As practical implementations continue to evolve, the human-centered design of wearable interfaces remains critical for ensuring user comfort, device usability, and sustained patient adherence, especially for elderly or digitally inexperienced users. Without good design and clear feedback, even advanced systems can fail in real use because users lose motivation over time.

In light of these trends and technological gaps, this review provides a systematic synthesis of 14 peer-reviewed original studies published between 2018 and 2025, covering diverse aspects of AI-enabled wearable systems for rehabilitation monitoring. By summarizing common sensor types, system architectures, algorithmic approaches, and reported clinical outcomes, the review aims to clarify what has been practically validated so far, what challenges remain unresolved, and what promising pathways exist for advancing precision rehabilitation in the coming years.

## 2. Methodology

This review provides a systematic analysis of published peer-reviewed literature that explores the application of AI-enhanced wearable technologies for personalized rehabilitation monitoring between 2018 and 2025. The main goal was to identify, screen, and synthesize original studies that describe how wearable sensor systems integrated with AI are used to track and optimize physiological and biomechanical parameters during recovery from surgical procedures, neurological conditions, or musculoskeletal disorders.

A structured search was conducted manually using Google Scholar and supported by searches in reputable databases such as Scopus, Web of Science, IEEE Xplore, and MDPI. The search terms included combinations like "wearable devices", "AI in rehabilitation", "smart monitoring", "EMG", "IMU", and "tele-rehabilitation". This approach ensured that the search captured multidisciplinary studies spanning biomedical engineering, clinical rehabilitation, and digital health technologies. In the initial phase, a total of 55 publications were identified. During the preliminary screening, 15 conference papers were excluded because they did not undergo full peer review, and 15 additional articles were removed due to incomplete methodological details, missing sensor descriptions, or lack of full-text availability. This left 25 studies for full-text screening. After detailed review, a further 11 articles were excluded because they did not specifically apply AI-enhanced wearable devices for rehabilitation monitoring or lacked sufficient experimental validation. As a result, 14 studies met all inclusion criteria.

These articles cover a range of rehabilitation contexts, including neurorehabilitation, orthopedic recovery, balance training for older adults, and remote physiotherapy using IoT and cloud-based monitoring platforms. Each selected article was systematically reviewed to extract key information such as:

- The types of sensors used (e.g., IMUs, surface EMG, ECG, textile-based sensors, pressure sensors)
- The machine learning methods applied (e.g., SVM, CNN, random forests (RF), RL;
- The design and scope of validation (pilot studies, clinical trials, laboratory tests)
- The main outcomes, including diagnostic accuracy, user adherence, real-time feedback capability, and overall impact on rehabilitation quality.

Methodological rigor, the clarity of system architecture, and consistency with the goal of personalized and adaptive rehabilitation were primary assessment criteria. Figure 1 below illustrates the step-by-step literature selection process using a PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram, showing how the initial pool of 55 records was narrowed down through staged screening and eligibility checks to the final 14 studies included in this review. The diagram clarifies the filtering decisions and provides transparency for reproducibility.

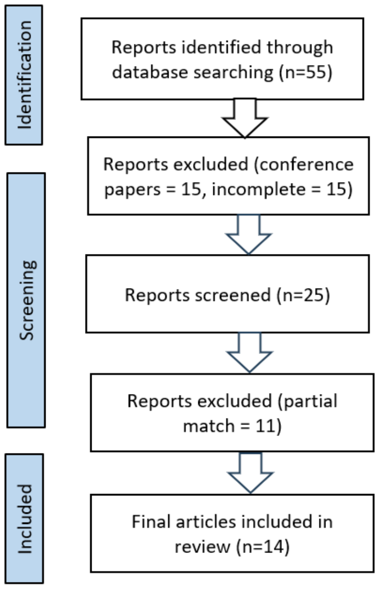


*Figure 1 – PRISMA flow diagram for literature selection*

## 3. Results

AI-powered wearable rehabilitation systems have demonstrated measurable benefits across musculoskeletal, neurological, postoperative, and sports-related recovery contexts by integrating multimodal sensors with diverse machine learning methods. In the domain of musculoskeletal rehabilitation, Mehek (2025) comprehensively reviewed how AI-driven wearable systems, integrating IMUs, EMG, ECG, and other biosensors, enhance home-based exercise monitoring and patient adherence. The paper highlights those modern intelligent wearables, supported by real-time predictive analytics and adaptive feedback loops, can deliver remote supervision comparable to in-person physiotherapy standards. By analyzing multiple case studies and real-world implementations, Mehek shows that AI-enabled smart wearables significantly improve monitoring accuracy, patient motivation, and rehabilitation outcomes [4].

Extending this direction, Ma et al. (2025) developed the SyncKnee system, which integrates EGaIn-polymer stretchable strain sensors capable of capturing subtle knee flexion and swelling patterns. A Random Forest classifier processes these signals, achieving a motion type classification accuracy of 98.48% when tested with 15 participants performing diverse activities, including standing, squatting, and lunging. This demonstrates the system's suitability for continuous osteoarthritis monitoring and timely swelling detection, offering personalized adjustments for daily activity levels and rehabilitation plans [5].

In neurorehabilitation, O'Brien et al. (2022) evaluated the predictive value of wearable IMU sensors placed on the waist and ankles of post-stroke patients. Using a balanced Random Forest model trained on short-distance walking trials, they achieved an AUROC of 0.988—significantly outperforming traditional clinical scales (AUROC= 0.905). This approach supports early, individualized treatment planning and prognosis by reliably predicting whether a patient can regain community-level ambulation post-discharge [2].

For sports injury prevention, Dave et al. (2025) (although published as a conference paper, if retained) explored a long-term physiotherapy monitoring framework for track and field athletes. Their system combines multimodal wearable sensors with survival analysis and Random Forest models to estimate overuse injury risks. Monitoring 11–18-year-old athletes over 56 weeks revealed how training frequency, surface hardness, and fatigue correlate with early injury onset, guiding coaches and clinicians in tailoring recovery loads and training conditions [6].

In the field of remote physiological monitoring, Kajornkasirat et al. (2025) presented a wearable IoT solution used primarily for post-viral recovery scenarios such as COVID-19. Their system combines $SpO_2$, heart rate, and temperature sensors, with data streams cross-validated against standard clinical devices ($r = 0.942$ for temperature, $r = 0.773$ for $SpO_2$, $r = 0.955$ for heart rate). Additionally, a Random Forest–powered emotion recognition module classified patients' mood states with 80% accuracy, allowing health professionals to interpret vital signs alongside psychosocial wellbeing during remote rehabilitation sessions [7]. To advance gait and balance assessment, Monge et al. (2023) designed a hybrid setup combining SensFloor® capacitive floor sensors, wearable IMUs, and deep learning algorithms (LSTM and GRU) to classify gait risk levels in real time. Tested with 14 volunteers, the system achieved classification accuracies over 75% in distinguishing abnormal gait patterns and was integrated with an augmented reality interface to deliver immediate visual feedback for postural correction and fall prevention [8].

Material science innovation has also been incorporated, as Chen et al. (2025) proposed a new class of self-healing and responsive smart materials embedded within wearable sensors. These materials extend device lifespan, maintain signal integrity under daily stress, and enable AI models to provide adaptive feedback for rehabilitation exercises. This approach shows how intelligent substrates can reduce device wear and maintain high-quality biosignal capture during long-term use [9].

Focusing on athlete-specific rehabilitation, Bin Wu (2024) demonstrated how AI-integrated wearables enhance recovery monitoring for track and field athletes. Their system captures movement kinematics and muscle workload data in real time, helping clinicians identify deviations from expected recovery trajectories and adjust training intensity. This timely feedback loop contributes to safer return-to-play decisions and minimizes reinjury risk [10].

From a system-level perspective, Secara and Hordiiuk (2024) described a conceptual Integrated Personal Health Monitoring System (IPHMS) that combines commercially available wearables (e.g., Apple Watch, Oura Ring) and smartphone applications with AI anomaly detection. They emphasized that, while real-time monitoring offers high level of personalization for chronic disease and stress management, unresolved challenges remain around interoperability with health records, ethical data governance, and user privacy protection. This highlights the need for robust legal and technical safeguards as AI-powered wearables become standard in personalized rehabilitation pathways [11].

Together, these studies demonstrate how AI-driven wearable systems can deliver precise motion tracking, physiological signal monitoring, early prognosis, and personalized feedback loops.

The combined evidence reinforces that integrating smart sensors, advanced machine learning, and user-centered design has strong potential for scalable, home-based rehabilitation across musculoskeletal, neuro, cardiopulmonary, and sports medicine applications.

A detailed overview of the key systems reviewed is presented in Table 1, summarizing the main sensor types, AI methods, and outcomes validated so far.

*Table 1 - Key characteristics and reported results of AI-based smart wearables for rehabilitation*

| Target Domain | Sensor Types | AI/ML Methods Used | Key Outcomes | Source |
|---|---|---|---|---|
| Rehabilitation (General) | Wearable sensors, robotics, VR/AR | ML algorithms, predictive analytics, adaptive therapy | Review: AI-driven wearables & intelligent systems enhance monitoring & personalization | Mehek (2025) [4] |
| Osteoarthritis (Knee) | EGaIn-polymer strain sensors | Random Forest | 98.48% accuracy for knee motion & swelling monitoring | Ma et al. (2025) [5] |
| Neurorehabilita-tion (Stroke) | IMU | Balanced Random Forest | AUROC = 0.988 vs. clinical AUROC = 0.905 | O'Brien et al. (2022) [2] |
| Sports Injury Prevention | Multimodal Wearables | Random Forest, Survival Analysis | Long-term injury risk prediction for athletes | Dave et al. (2025) [6] |
| Physiological Monitoring | $SpO_2$, HR, Temp | Random Forest (Emotion Recognition) | High vital sign correlation; 80% emotion classification | Kajornkasirat et al. (2025) [7] |
| Gait & Balance Therapy | SensFloor®, IMU | LSTM, GRU | >75% gait risk classification; AR visual feedback | Monge et al. (2023) [8] |
| Smart Materials Rehab | Self-healing adaptive sensors | Adaptive AI Feedback | Longer lifespan, real-time adaptive rehab | Chen et al. (2025) [9] |
| Sports Rehab | IMU, EMG | Machine Learning | Faster recovery insights for athletes | Bin Wu (2024) [10] |
| System-Level IPHMS | Multi-device integration | AI Anomaly Detection | Privacy risks; interoperability challenges | Secara & Hordiiuk (2024) [11] |

## 4. Discussion

The integration of artificial intelligence and advanced wearable sensors into rehabilitation strategies represents an important step towards more precise, patient-tailored, and widely accessible care. Table 2 summarizes the reviewed studies collectively demonstrate how AI-enhanced wearables are shaping new standards for monitoring, clinical decision-making, and patient engagement across diverse rehabilitation contexts.

First, sensor–AI integration has emerged as a core enabler of higher diagnostic accuracy and continuous monitoring. The SyncKnee system by Ma et al. (2025) combined highly stretchable polymer strain sensors with a Random Forest classifier to monitor both knee joint flexion and swelling. By achieving over 98% classification accuracy across various motion types, the system shows how advanced materials and robust algorithms can deliver fine-grained biomechanical insights directly at the point of care [5]. Similarly, Monge (2023) demonstrated that combining ambient SensFloor® sensors with IMUs and sequence-based deep learning models (LSTM and GRU) allows gait patterns and fall-risk levels to be classified with over 75% accuracy, providing real-time AR-based feedback to users and therapists [8]. These examples underline how multi-modal sensor streams and advanced learning models complement each other to capture complex patient motion profiles that traditional methods may overlook.

Second, remote rehabilitation and accessibility benefits were consistently validated. Mehek et al. (2025) demonstrated that AI-driven smart wearable systems, integrating IMU, EMG, and ECG sensors, can provide personalized real-time monitoring and adaptive feedback, supporting effective home-based rehabilitation and improving patient adherence [4]. The author Thirumangai et al. (2024) highlighted a fully remote physical therapy platform using computer vision pose estimation, CNNs, and RNNs to automatically analyze patient movements and deliver immediate feedback through telehealth interfaces. This system proved highly responsive and adaptable for physiotherapy monitoring, even for patients in underserved regions [12]. Kajornkasirat et al. (2025) extended this perspective by combining multiple physiological sensors ($SpO_2$, heart rate, temperature) with an AI-driven emotion recognition module. Their system maintained strong measurement agreement with gold-standard medical devices ($r = 0.955$ for heart rate, $r = 0.773$ for $SpO_2$), while the emotion module achieved 80% classification accuracy, highlighting how integrated affective and physiological monitoring can enrich remote patient supervision [7].

Third, personalization and user engagement were advanced through predictive analytics and adaptive feedback loops. Dave et al. (2025) tested a wearable-based monitoring system for young athletes over a 56-week period, using Random Forest models and survival analysis to identify training and environmental factors driving lower-limb injury risks. This long-term study showed that real-time sensor data could fine-tune individualized recovery plans and proactively reduce overuse injuries [6]. The author, Bin Wu (2024) demonstrated that AI-enabled wearables for track and field athletes can continuously monitor biomechanical loads and joint flexibility, allowing physiotherapists to tailor rehabilitation programs dynamically and shorten recovery timelines by addressing deviations early [10].

Despite these innovations, key limitations persist. Secara and Hordiiuk (2024) emphasized that integrating multiple consumer-grade wearables and smartphone data flows into unified AI systems introduces substantial privacy and governance risks – especially given the lack of robust encryption and data-sharing protocols [11]. Qin and Wen (2025) critically assessed smart wearables for postoperative lower limb fracture care, pointing out unresolved comfort and usability challenges that can hinder adherence, particularly when devices must be worn long term or during sleep [13].

Additionally, Shajari et al. (2023) warned that many promising AI-powered wearables remain under-validated, with few large-scale clinical trials to prove real-world effectiveness across diverse patient populations. They called for stronger cross-disciplinary collaboration to standardize sensor calibration, interoperability, and algorithm benchmarking [3]. Finally, Nairn et al. (2025) provided a comparative scoping review of 17 balance rehabilitation systems for older adults, showing that while motion tracking and gamification were prevalent, only one system employed AI techniques. This finding points to an ongoing technology gap between research prototypes and commercial rehabilitation tools, particularly regarding real-time intelligent feedback and remote adaptability [14].

These studies confirm that AI-enabled wearables have moved well beyond concept stage—delivering accurate diagnostic insights, facilitating remote care, and helping patients stay engaged through adaptive interfaces. Yet, their broad adoption still requires overcoming practical barriers around user comfort, data protection, system integration with electronic health records, and standardization of clinical validation. Addressing these gaps will demand not only technical refinement but also coordinated efforts among engineers, clinicians, regulators, and patients themselves, ensuring that smart rehabilitation solutions remain trustworthy, scalable, and truly personalized.

*Table 2 – Summary of AI-enhanced wearable systems for rehabilitation*

| Theme | System / Method | Key Outcomes | Source |
|---|---|---|---|
| Sensor–AI Integration | SyncKnee (EGaIn + RF); IMU + SensFloor + LSTM/GRU | High-precision joint motion and gait classification (75–98% accuracy) | Ma et al. (2025); Monge (2023) [5, 8] |
| Remote Rehab & Accessibility | Multi-sensor IMU, EMG, ECG with AI DSS; vital sign tracking + RF; CNN/RNN adaptive visual feedback | Validated AI-driven remote rehab, real-time monitoring, personalized adaptive feedback | Mehek (2025); Kajornkasirat et al. (2025); Thirumangai et al. (2024) [4,7,12] |
| Personalization & Engagement | Wearable monitoring + RF + survival analysis | Early injury prediction; dynamic adaptation of therapy loads | Dave et al. (2025); Bin Wu (2024) [6,10] |
| Challenges & Gaps | Multi-device fusion; lower limb post-op wearables; balance rehab scoping | Privacy, comfort, lack of large trials, minimal AI use in commercial solutions | Shajari et al. (2023); Secara & Hordiiuk (2024); Qin & Wen (2025); Nairn et al. (2025) [3,11,13,14] |

## 7. Conclusions

This review shows the strong potential of AI-integrated wearable systems in advancing personalized rehabilitation practice. Across musculoskeletal, neurological, and cardiopulmonary applications, these new technologies show strong potential of adaptability, diagnostic accuracy, and patient-centered utility. Evidence synthesized from recent high-quality studies confirms that combining multimodal sensor arrays — such as IMUs, surface EMG, strain sensors, and other biosignal monitors — with robust machine learning algorithms including Random Forest, long short-term memory (LSTM) networks, and CNNs delivers significant improvements in clinical assessment, real-time feedback, and individual therapy adjustment. Wearable systems such as the SyncKnee platform for knee osteoarthritis monitoring, SensFloor-based gait and balance trackers, and vital-sign-integrated smart devices have demonstrated diagnostic accuracy between 75% and 98%, frequently surpassing or complementing conventional clinical assessments. These results indicate that AI-powered wearable technologies have strong potential to reduce the burden on healthcare facilities by enabling decentralized, home-based rehabilitation models that maintain high-quality monitoring outside traditional clinical settings.

Persistent challenges must still be addressed to achieve widespread clinical adoption. Issues such as long-term wearer comfort, data privacy and security, sensor calibration, interoperability with existing health record infrastructures, and the lack of unified clinical validation standards continue to limit large-scale implementation. Regulatory clarity, universal technical standards, and robust evidence from large-scale, diverse patient trials will be critical to demonstrate sustained safety, clinical efficacy, and cost-effectiveness over time.

Future research directions should therefore emphasize longitudinal investigations, the refinement of cross-platform interoperability, and the development of highly personalized, behavior-aware feedback systems to ensure that intelligent wearables truly deliver on their promise to improve rehabilitation outcomes in real-world, patient-centered healthcare environments.

**Conflicts of Interest.** The authors declare no conflicts of interest.

**Funding**. This research was funded under project BR24992820 within the scientific and technical program “Innovative medical technologies and devices to improve surgical interventions in prosthetics and rehabilitation in the field of orthopedics and medical rehabilitation”.

**Author Contributions.** Conceptualization - R.B., T.A., A.B., B.I.; Data Curation - T.A., A.B., B.I., N.K.; Formal Analysis - T.A., A.B., B.I., K.O., N.K.; Funding Acquisition R.B., B.I., K.O., N.K.; Investigation R.B., A.B., N.K.; Methodology - R.B., T.A., A.B., B.I., K.O., N.K.; Project Administration - B.I., K.O.; Resources T.A., A.B., N.K.; Software - R.B., B.I., K.O., N.K.; Supervision - B.I., K.O.; Validation T.A., A.B., N.K.; Visualization - R.B., B.I., K.O., N.K.; Writing – Original Draft - T.A., A.B., N.K.; Writing – Review & Editing R.B., B.I., K.O., N.K.

All authors have read and agreed to the published version of the manuscript.

## References

1. Deng, Z., Guo, L., Chen, X., & Wu, W. (2023). Smart wearable systems for health monitoring. Sensors, 23(5), 2479. https://doi.org/10.3390/s23052479
2. O'Brien, M. K., Shin, S. Y., Khazanchi, R., Fanton, M., Lieber, R. L., & Ghaffari, R. (2022). Wearable sensors improve prediction of post-stroke walking function following inpatient rehabilitation. IEEE Journal of Translational Engineering in Health and Medicine, 10, 1–10. https://doi.org/10.1109/JTEHM.2022.3208585
3. Shajari, S., Kuruvinashetti, K., Komeili, A., & Sundararaj, U. (2023). The emergence of AI-based wearable sensors for digital health technology: A review. Sensors, 23(23), 9498. https://doi.org/10.3390/s23239498
4. Mehek, A. (2025). The Evolution of AI in Rehabilitation: Enhancing Recovery with Intelligent Systems. JOIREM, 5(6). Available at: https://www.researchgate.net/publication/392841593
5. Ma, Z., Fang, L., Fang, C., Chai, B., Zheng, Z., & Wang, S. J. (2025). Intelligent wearable system design for personalized knee motion and swelling monitoring in osteoarthritis care. Cell Reports Physical Science, 6(3), 102438. https://doi.org/10.1016/j.xcrp.2025.102438
6. Dave, Y., Natarajan, D. R., Jani, H., Khant, A., Adwani, P., & Mehta, J. (2025). AI Driven Personalized Rehabilitation System Using Wearable Sensors for Real Time Physiotherapy Monitoring. Proceedings of the 2025 IEEE Conference on Emerging Engineering Technologies (CE2CT), Article No. 10939054. IEEE. https://doi.org/10.1109/CE2CT64011.2025.10939054
7. Kajornkasirat, S., Sawangwong, C., Puangsuwan, K., Chanapai, N., Phutthamongkhon, W., & Puttinaovarat, S. (2025). Integrating AI-Driven Predictive Analytics in Wearable IoT for Real-Time Health Monitoring in Smart Healthcare Systems. Applied Sciences, 15(8), 4400. https://doi.org/10.3390/app15084400
8. Monge, J., Ribeiro, G., Raimundo, A., Postolache, O., & Santos, J. (2023). AI-Based Smart Sensing and AR for Gait Rehabilitation Assessment. Information, 14(7), 355. https://doi.org/10.3390/info14070355
9. Chen, S., Fan, S., Qiao, Z., Wu, Z., Lin, B., Li, Z., Riegler, M. A., Wong, M. Y. H., Opheim, A., Korostynska, O., & Nielsen, K. M. (2025). Transforming Healthcare: Intelligent Wearable Sensors Empowered by Smart Materials and Artificial Intelligence. Advanced Materials, https://doi.org/10.1002/adma.202500412
10. Wu, B. (2024). Real Time Monitoring Research on Rehabilitation Effect of Artificial Intelligence Wearable Equipment on Track and Field Athletes. EAI Endorsed Transactions on Pervasive Health and Technology, 10, 5150. https://doi.org/10.4108/eetpht.10.5150
11. Secara, I.-A., & Hordiiuk, D. (2024). Personalized Health Monitoring Systems: Integrating Wearable and AI. Journal of Intelligent Learning Systems and Applications, 16(2), Article 162004. https://doi.org/10.4236/jilsa.2024.162004
12. Thirumangai, S., Thilagan, P., & Anitha, N. (2024). Smart Remote Physical Therapy: Deep Learning-Based Patient Monitoring. In 2024 IEEE 1st International Conference on Green Intelligent and Energy-Sustainable Technologies (GIEST) (pp. 1–6). IEEE. https://doi.org/10.1109/GIEST62955.2024.10959779
13. Qin, X., & Wen, Q. (2025). Application progress and future prospects of smart wearable devices in postoperative rehabilitation of lower limb fractures: A mini review. Current Problems in Surgery, 67, 101755. https://doi.org/10.1016/j.cpsurg.2025.101755

14. Nairn, B., Tsakanikas, V., Gordon, B., Karapintzou, E., Kaski, D., Fotiadis, D. I., & Bamiou, D. E. (2025). Smart wearable technologies for balance rehabilitation in older adults at risk of falls: Scoping review and comparative analysis. JMIR Rehabilitation and Assistive Technologies, 12, e69589. https://doi.org/10.2196/69589

# Жасанды интеллект негізіндегі смарт-киілетін жүйелерді жекелендірілген оңалтуды мониторингте қолдану

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## Түйіндеме

Жекелендірілген әрі тиімді оңалту әдістеріне деген сұраныстың артуы жасанды интеллект негізіндегі ақылды киілетін құрылғыларды дамытуға түрткі болды. Мұндай жүйелер науқастардың денсаулығын нақты уақытта бақылауға, болжауға және бейімделген кері байланыс беруге мүмкіндік жасап, нейро-бұлшықет және операциядан кейінгі оңалту нәтижелерін жақсартуға септігін тигізеді.

Осы шолуда 2018–2025 жылдар аралығында жарияланған, рецензияланған 14 ғылыми мақалаға жүйелі талдау жүргізілді. Зерттеулер IEEE, MDPI және басқа да ғылыми дерекқорлардан құрылымдалған ізденіс арқылы іріктелді және жасанды интеллект көмегімен оңалтуды жетілдіретін киілетін құрылғыларға арналды. Көп қолданылатын алгоритмдер қатарында қолдау векторлық машиналар (SVM), конволюциялық нейрондық желілер (CNN) және күшейтпелі оқыту (RL) әдістері бар. Олар жүріс-тұрысты талдау, буын қозғалысын тану, бұлшықет белсенділігін бақылау және қалпын қадағалау сияқты қызметтерді қамтамасыз етеді. Сонымен қатар, IoT сенсорлық желілерімен, бұлттық платформалармен және телемедициналық интерфейстермен интеграция кеңінен енгізілгені анықталды. Шолу нәтижесі көрсеткендей, AI-технологиялармен жабдықталған киілетін құрылғылар пациенттердің оңалтуға бейімділігін арттырып, мониторинг дәлдігін күшейтеді және терапияны жекелеп бейімдеуге ықпал етеді. Дегенмен, деректердің қауіпсіздігі, сенсорларды калибрлеу, өзге жүйелермен үйлесімділігі мен пайдаланушылардың ұзақ мерзімді қызығушылығын сақтау мәселелері әлі де өзекті болып отыр. Жалпы алғанда, интеллектуалды киілетін құрылғылар дерекке негізделген жекелендірілген оңалтуда маңызды рөл атқаратыны дәлелденді.

**Түйін сөздер**: киілетін құрылғылар, жасанды интеллект, жекелендірілген оңалту, қашықтықтан мониторинг, жүріс-тұрысты талдау, машиналық оқыту, телемедицина, смарт денсаулық сақтау.

# Носимые системы на базе искусственного интеллекта для персонализированного мониторинга в процессе реабилитации

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## Резюме

Растущий спрос на персонализированные и эффективные реабилитационные подходы стимулирует разработку интеллектуальных носимых систем с элементами искусственного интеллекта. Эти устройства позволяют в режиме реального времени отслеживать состояние здоровья пациентов, прогнозировать возможные отклонения и предоставлять адаптивную обратную связь, что способствует улучшению клинических результатов при нейро-мышечной и послеоперационной реабилитации.

Настоящий обзор охватывает 14 рецензируемых публикаций, вышедших в период с 2018 по 2025 годы, включая клинические исследования, когортные наблюдения и инженерные разработки. Отобранные работы найдены с помощью структурированного поиска в базах IEEE, MDPI и других авторитетных научных ресурсах и посвящены носимым устройствам для реабилитации с поддержкой искусственного интеллекта (ИИ). Наиболее часто используемые алгоритмы включают машины опорных векторов (МОВ), сверточные нейронные сети (СНС) и методы обучения с подкреплением. Эти технологии обеспечивают такие функции, как анализ походки, распознавание движений суставов, отслеживание активности мышц и контроль осанки. Кроме того, широко описана интеграция с IoT-сетями сенсоров, облачными платформами и телемедицинскими сервисами. Результаты обзора показывают, что носимые системы с поддержкой ИИ значительно повышают приверженность пациентов к терапии, точность мониторинга и индивидуализацию лечебных мероприятий. Тем не менее сохраняются проблемы безопасности данных, калибровки сенсоров, совместимости с другими системами и долгосрочного удержания пользователей. В целом доказано, что интеллектуальные носимые технологии играют важную роль в поддержке персонализированной, основанной на данных реабилитации.

**Ключевые слова:** носимые устройства, искусственный интеллект, персонализированная реабилитация, дистанционный мониторинг, анализ походки, машинное обучение, телемедицина, умное здоровье.