Proceedings of the 6th International Conference on Biological Engineering and Medical Science
DOI: 10.54254/2753-8818/2026.37986

Application of Wearable Devices in Rehabilitation for Lower Limb Injuries

Jingxuan Li

School of Physical Education, Wuxi College, Wuxi, China
Jingxuanli_2026@outlook.com

Abstract. Lower limb injuries are common among athletes, yet rehabilitation assessment has long been fragmented, subjective, and short on continuous objective data. Wearable devices, worn on the body or embedded in clothing, capture kinematic and physiological signals around the clock and can turn them into quantified, real-time feedback. Drawing on evidence from inertial measurement units (IMUs), surface electromyography (sEMG), and photoplethysmographic pulse wave sensors (PPG), this paper reviews how these technologies serve three rehabilitation phases: acute care, training, and return to sport. In the acute phase they define safe activity boundaries; in training they support movement correction and progress tracking; in the return phase they inform clearance decisions and recurrence prevention. The evidence suggests wearables are moving rehabilitation decisions from clinical judgment toward data-driven assessment, although limited clinical validation, degraded accuracy in dynamic settings, injury-unspecific algorithms, and data privacy concerns still stand in the way. Multimodal fusion, deep learning, closed-loop prescription systems, and privacy-preserving computing are the most promising directions ahead.

Keywords: Wearable devices, lower limb injuries, rehabilitation, inertial measurement unit, surface electromyography

1. Introduction

Lower limb injuries are structural damage or functional loss in the bones, joints, muscles, tendons, ligaments, or nerves of the hip, knee, ankle, and foot. They can be acute—a lateral ankle ligament sprain, an anterior cruciate ligament (ACL) rupture, a tibia fracture—or chronic, as with patellar tendonitis and Achilles tendinopathy. Among athletes they are extremely common. In an umbrella review that pooled 13 reviews and 148 primary studies, Knierim Correia et al. traced running-related injuries to training characteristics, lifestyle, and biomechanics, with sudden jumps in training volume and a history of prior injury carrying the largest effect sizes [1]. Dillon et al.'s prospective work similarly found high annual incidence of lower limb injury in recreational runners [2]. The injury profile differs by sport: basketball players sprain ankles most often, soccer players tear knee ligaments, and long-distance runners accumulate overuse problems. Rehabilitation plans therefore have to fit the specific injury and the demands of the sport, not follow a single standard path.

© 2026 The Authors. This is an open access article distributed under the terms of the Creative Commons Attribution License 4.0 (https://creativecommons.org/licenses/by/4.0/).

DOI: 10.54254/2753-8818/2026.37986

Traditional rehabilitation is limited in three ways. Assessment is fragmented: once patients go home, progress rests largely on what they report. Pain relief is also routinely mistaken for recovery: patients return to full training before ligaments have healed or strength has caught up, and reinjury follows. Therapists themselves disagree; two clinicians can watch the same single-leg hop and reach different return-to-play verdicts. Underneath all three problems sits one shared cause: the rehabilitation process produces no continuous, objective data, so a lasting information gap persists between patient and clinician. Tan et al.'s scoping review reports reinjury rates above 20% after ACL reconstruction even with standardized surgery and rehabilitation, attributing much of this to visual assessment and a lack of objective data outside the lab [3].

Wearable devices are portable instruments that attach to the body or sit inside clothing and keep collecting kinematic or physiological signals. The common types are inertial measurement units (IMUs), surface electromyography (sEMG) sensors, and photoplethysmographic pulse wave sensors. Where a clinic visit captures only a snapshot, a wearable keeps recording through daily life, which gives three advantages at once: monitoring is continuous, measurements are objective and quantifiable, and feedback reaches the patient in real time. That shift from point-in-time to continuous data is exactly what addresses the fragmentation of traditional assessment.

Sports rehabilitation does not wait for complete healing and then restart activity. It begins right after injury as a continuous process of functional training, movement correction, and load management that gradually restores athletic capacity and lowers the chance of reinjury. The process is usually described in three phases: acute, training, and return to sport, and each phase lines up naturally with what wearable monitoring can provide. Following this framework, the article reviews how the three sensor types are used in each phase, weighs the evidence behind them and their current limitations, and discusses optimization directions in light of both their strengths and the practical obstacles, in the hope of informing clinical choices and future studies.

2. Monitoring principles

Rehabilitation wearables all follow the same workflow: collect a signal, process it, and feed something back. The sensor turns a physiological signal into an electrical one, the device extracts the features that matter and compares them with preset thresholds, and when a limit is crossed the user gets a vibration or a sound. The point of all this is worth stating plainly: monitoring exists to turn rehabilitation risk and progress into signals a patient can perceive and act on, not to accumulate data for its own sake. That principle is common to all three sensor types.

2.1. Inertial measurement units for joint motion monitoring

An inertial measurement unit (IMU) combines accelerometers and gyroscopes and can report joint angles, step frequency, ground contact time, and movement symmetry. Its most straightforward use is watching whether joint motion stays inside safe limits. In a lateral ankle sprain, for example, an IMU fixed to the lower leg and foot can be given an inversion threshold; if walking pushes past it, the wearer feels a vibration. The therapist's clinical judgment, in effect, goes home with the patient. Calibration, though, sets a limit on how much the measurements can be trusted. In a comparison of seven calibration methods, knee range of motion measured during running and single-leg hops differed from optical motion capture by anywhere between 0.1° and 24.1° [4]. Clinicians therefore need to pair the calibration procedure with the movement being measured, and a device should be validated for its intended use before it reaches patients—more important than chasing nominal accuracy. Meta-analytic evidence supports the approach: in ankle injury rehabilitation, wearables

DOI: 10.54254/2753-8818/2026.37986

produced a standardized mean difference of 0.66 in functional performance and 0.78 in ankle function scores, both statistically significant [5].

2.2. Surface electromyography (sEMG) sensors for muscle activation monitoring

Surface electromyography sensors pick up muscle electrical activity through skin electrodes, showing when a muscle fires, how hard, and whether the two sides stay symmetrical. A common problem in rehabilitation is that patients believe they are pushing hard when in fact they are overusing compensatory muscles and under-activating the target ones; sEMG turns that invisible effort into a visible trace. In one randomized trial, 40 patients after ACL reconstruction were split into a feedback group and a control group (20 each). Both followed standard rehabilitation, but the feedback group also watched their sEMG signal in real time for 30 minutes, three times a week, over four weeks. Their quadriceps strength rose from (14.9±1.2) kg to (19.5±1.1) kg, a gain of about 4.6 kg (roughly 31%); the control group moved only from (15.0±1.1) kg to (16.0±1.2) kg, a change that was not statistically significant [6]. What EMG feedback really buys is precision: instead of a therapist saying "push harder," patients see what correct effort looks like, which makes the technique especially useful for unsupervised home training.

2.3. Photoplethysmographic pulse wave sensors for training load monitoring

Photoplethysmographic pulse wave sensors use optical reflection to estimate heart rate and heart rate variability; they are the familiar technology inside wrist-worn watches and are used to track training intensity and fatigue. The stakes are real on both sides: too little load and recovery stalls, too much and the injury gets worse, so heart rate is the handiest window into internal load. In a six-week study of 24 recreational runners, those who became overfatigued showed nighttime heart rate up by 3.2% and heart rate variability down by 0.7%, while runners who adapted normally moved in the opposite direction; heart rate, in other words, can separate adequate training from overtraining [7]. The technology has accuracy limits, though. In a ten-day validation against gold-standard ECG in 25 participants, heart rate error during sleep stayed under one beat per minute, but heart rate variability error during activity ran 14% to 51% higher than at rest [8]. So heart rate is best read as an individual trend rather than an absolute number, and in dynamic settings it works better as a supporting metric than as the primary one. Taken together, the three sensor families cover the full picture: kinematics, neuromuscular control, and cardiorespiratory load.

3. Phased applications

3.1. Acute phase: management of activity boundaries

The acute phase is about protecting injured tissue while keeping the patient moving within safe limits. The danger to guard against is early weight bearing and a quick return to full activity. With an ankle sprain, an IMU-equipped brace watches inversion and eversion angles and vibrates when they go beyond threshold, turning the vague instruction to "rest" into a concrete, enforceable boundary. Acute-phase care itself is moving away from simple immobilization toward controlled movement. One protocol, the SMART sensorimotor training program for first-time acute lateral ankle sprains, packages six weeks of sensory stimulation, range-of-motion work, activation and balance, resistance, and functional integration; the randomized trial plans to enroll 78 patients and use the CAIT self-reported ankle function score as its primary endpoint, but only the study protocol has been published so far [9]. The value of acute-phase wearables is precisely this: they add a boundary

DOI: 10.54254/2753-8818/2026.37986

and a feedback loop to rest, so patients keep up the movement needed to avoid muscle atrophy and stiff joints without aggravating the injury.

3.2. Movement correction and progress quantification during training

The training phase aims at functional restoration, and much of it happens at home, where a therapist cannot stand by. Real-time feedback and automatic recording therefore carry real weight here. Quadriceps rehabilitation after ACL surgery is the most mature use of sEMG feedback: the trial described earlier showed significant gains in strength and functional scores after four weeks [6]. Doing straight-leg raises or terminal knee extensions, the patient watches live activation curves for the vastus medialis and lateralis; if the medial side lags, the display says to shift the force direction. For chronic ankle instability, meta-analyses report that biofeedback moves the center of plantar pressure and cuts peak lateral pressure, and auditory feedback appears to work better than visual [10]—a reminder that device design should favor what fits a home setting, not the most elaborate technology. Progress can be quantified as well. A systematic review covering 18 studies and 1,754 patients found all six randomized controlled trials showed wearable feedback increased physical activity. In one TKA study, the intervention group took 1,798 more steps per day and logged 73.4 more minutes of weekly moderate-to-vigorous activity than controls [11]. Two orthopedic RCTs went further and found device-guided home rehabilitation no worse than traditional physical therapy; smartphone-driven remote rehabilitation after TKA, for instance, matched conventional therapy at 12 months [11]. The direction is clear: training-phase devices are turning from passive recorders into supervisory assistants that encode the therapist's instructions as concrete, moment-by-moment standards for every exercise.

3.3. Assessment and recurrence prevention during return-to-activity phase

The return-to-activity phase asks one hard question: can this patient resume sport safely, and will the injury come back? The usual tests—single-leg hop, Y-balance—depend on the naked eye, and mild asymmetry slips past. Yona et al. followed 26 patients after ACL reconstruction (18 of them through five months) as they climbed and descended 20 real stairs outside the lab wearing seven IMUs. At three months, the operated knee flexed 11.3° less than the healthy side going up and 6.3° less coming down. By five months the gap on ascent had narrowed to 4.7°, but the descent deficit remained [12]. Real-world monitoring, in other words, exposes impairments that a single clinic visit can miss, and clearing a patient on outpatient testing alone leaves room for reinjury. On the prevention side, a trial randomized 220 runners and gave the intervention group real-time pressure-insole feedback, cutting the injury risk ratio to 0.53 [13]. A third of the participants, though, got nothing from the device because it was set up incorrectly—usability and adherence matter as much as the hardware, which argues for zero-setup products.

4. Advantages and challenges of application

Wearable devices bring three practical advantages to rehabilitation. The first is continuity. Devices worn in daily life log gait and activity data day after day, capturing far more than any self-report scale can; after total knee arthroplasty, for instance, patients can be followed at home through remote gait monitoring [14]. Objectivity matters just as much: joint angles, electromyographic activity, and heart rate are numbers rather than impressions, so therapist judgment varies less. And because feedback arrives in real time, patients can correct themselves mid-session instead of waiting

DOI: 10.54254/2753-8818/2026.37986

for the next clinic visit. Taken together, these strengths are moving rehabilitation decisions away from clinical intuition toward recorded evidence.

Moving these devices into clinical practice is not straightforward. Consumer-grade products, for a start, have seen little clinical validation; most run on algorithms built from laboratory data on healthy young adults, and their reliability on patients is an open question. One waist-mounted IMU, for example, classified gait accurately 96% of the time in the lab but only 89% in real-world conditions [15]. PPG sensors, as noted, lose precision during movement, which limits them in high-intensity training [8]. Algorithms are also far from injury-specific: configurations and processing differ widely across conditions and no standard exists [16]. And the data they collect is sensitive: a review of 72 papers put the re-identification rate of de-identified wearable data above 86%, sometimes from one second of recording [17]. Getting devices from the bench to the bedside therefore demands standardized validation and regulation, not just better hardware.

5. Optimization strategies

5.1. Multimodal sensing fusion and cross-validation

Each sensing modality covers some things and misses others. IMUs say nothing about muscle activation, sEMG cannot measure joint moments, and PPG has no kinematic information. Collecting several modalities at once lets them fill in for each other and check one another. A systematic review of 66 studies concluded that sensor fusion markedly improves gait analysis, with the added electromyography signal bringing the clearest gain [18]. Fusion does not depend on clever algorithms so much as on a shared protocol for synchronized collection: only when multi-source data sit on a common timeline can they form a complete rehabilitation picture.

5.2. Deep learning for injury-specific feature extraction

Traditional algorithms rely on hand-crafted features and struggle to pull injury-specific information out of complex gait signals. Deep learning does better: convolutional and recurrent neural networks, combined, can learn from gait data end to end [16]. The clinical payoff shows up on three levels. At the feature level, the network extracts kinematic patterns tied to a particular injury straight from raw signals. At the task level, it grades the quality of movements like single-leg hops and stair climbing, turning symmetry assessment from a subjective call into an objective score. At the prediction level, it can combine injury history with current load to warn about reinjury risk for an individual patient. The catch is data: training these models needs large annotated datasets. Some teams have already pooled 2,885 days of public data from 790 participants as a resource for model development [19]. Cost-wise the picture is front-loaded: the early money goes into annotation and training, but once a model matures, running it on a phone makes each assessment nearly free. A cloud-training, edge-inference arrangement lowers hardware costs for institutions, and patients who can assess themselves at home make fewer trips to the hospital. In short, the approach is expensive at first and cheap at scale.

5.3. Integration with rehabilitation prescription systems to form a closed loop

Most wearable devices today show monitoring data but offer no training advice, which leaves their value largely untapped; in a survey, 63% of therapists said they wanted continuous monitoring data fed straight into electronic medical records [19]. The next step is to link devices to rehabilitation

DOI: 10.54254/2753-8818/2026.37986

prescription systems. Data from the wearable syncs automatically to the platform, the platform adjusts training parameters against the preset protocol and keeps the therapist informed, and the loop of collect, assess, adjust, and re-collect closes. A system might, for instance, read the patient's range of motion and strength for the day, hold back progression when targets are missed, and move to the next stage when they are met. The costs divide into three parts: developing the prescription platform, integrating the systems, and the device terminals themselves. The platform and interface are one-time expenses whose per-patient share shrinks as enrollment grows, while patients save on visits and overall healthcare costs. The point of the closed loop is simple: data re-enters the decision process instead of piling up in an isolated recorder.

5.4. Strengthening data privacy protection

Wearable health data is deeply personal, so privacy protection has to work on two fronts at once. On the technical side, federated learning lets models train on the device itself, so raw data never has to leave it for a central server, and techniques like differential privacy and homomorphic encryption add another layer of security. On the management side, dedicated regulations should be introduced sooner rather than later to define what can be collected and who may use it, and to guarantee patients the right to see and delete their own data.

On accuracy, Forsyth et al. validated a rehabilitation sensor for total knee arthroplasty and found knee flexion angle errors within 3 degrees of the Vicon motion capture system [20]. Medical-grade devices are thus closing in on laboratory gold standards, which gives the strategies above a realistic hardware base.

6. Conclusion

Wearable devices are shifting lower-limb injury rehabilitation from fragmented, subjective assessment to continuous, objective monitoring, and the evidence lines up by sensor type. IMUs track joint angles and gait symmetry in real time, with solid support in restricting activity after acute ankle sprains and in evaluating patients after ACL reconstruction. sEMG biofeedback reactivates the quadriceps after ACL surgery and corrects the gait patterns of chronic ankle instability, and randomized trials show measurable strength gains within weeks. PPG-based heart rate monitoring offers a convenient handle on exercise intensity and fatigue. Phase by phase the roles are distinct: acute-phase wearables set safe activity boundaries, training-phase devices correct movement and quantify progress, and return-phase tools provide objective clearance criteria and help prevent recurrence.

None of this means wearables can replace rehabilitation physicians or physical therapists. Consumer-grade devices still lack clinical validation, accuracy drops in dynamic settings, algorithms are not injury-specific, and privacy risks remain unresolved; these four problems have to be tackled together across hardware, algorithms, and regulation. The most promising lines of work are multimodal sensor fusion, deep-learning feature extraction, closed-loop prescription systems, and privacy-preserving computing. As medical-grade accuracy improves and public datasets grow, wearable devices are likely to move from helpful accessories to standard equipment in lower-limb injury rehabilitation.

DOI: 10.54254/2753-8818/2026.37986

References

[1] Correia, C. K., Machado, J. M., Dominski, F. H., de Castro, M. P., de Brito Fontana, H., & Ruschel, C. (2024). Risk factors for running-related injuries: An umbrella systematic review. *Journal of Sport and Health Science, 13*(6), 793–804. https://doi.org/10.1016/j.jshs.2024.04.011

[2] Dillon, S., Burke, A., Whyte, E. F., O'Connor, S., Gore, S., & Moran, K. A. (2023). Running towards injury? A prospective investigation of factors associated with running injuries. *PloS One, 18*(8), e0288814. https://doi.org/10.1371/journal.pone.0288814

[3] Tan, T., Gatti, A. A., Fan, B., Shea, K. G., Sherman, S. L., Uhlrich, S. D., Hicks, J. L., Delp, S. L., Shull, P. B., & Chaudhari, A. S. (2023). A scoping review of portable sensing for out-of-lab anterior cruciate ligament injury prevention and rehabilitation. *NPJ Digital Medicine, 6*(1), 46. https://doi.org/10.1038/s41746-023-00782-2

[4] Ekdahl, M., Loewen, A., Erdman, A., Sahin, S., & Ulman, S. (2023). Inertial measurement unit sensor-to-segment calibration comparison for sport-specific motion analysis. *Sensors (Basel, Switzerland), 23*(18), 7987. https://doi.org/10.3390/s23187987

[5] Wang, X., Qiu, J., & Fong, D. T. P. (2023). The applications of wearable devices in the rehabilitation of ankle injuries: A systematic review and meta-analysis. *Medicine in Novel Technology and Devices, 17*, 100184.

[6] Norozian, B., Arabi, S., Marashipour, S. M., Khademi Kalantari, K., Akbarzadeh Baghban, A., Kazemi, S. M., & Jamebozorgi, A. A. (2023). Recovery of quadriceps strength and knee function using adjuvant EMG-BF after primary ACL reconstruction. *Journal of Lasers in Medical Sciences, 14*, e6. https://doi.org/10.34172/jlms.2023.06

[7] Nuuttila, O. P., Uusitalo, A., Kokkonen, V. P., Weerarathna, N., & Kyröläinen, H. (2024). Monitoring fatigue state with heart rate-based and subjective methods during intensified training in recreational runners. *European Journal of Sport Science, 24*(7), 857–869. https://doi.org/10.1002/ejsc.12115

[8] Assessment of physiological signals from photoplethysmography sensors compared to an electrocardiogram sensor: A validation study in daily life. *Sensors (Basel, Switzerland), 24*(21), 6826. https://doi.org/10.3390/s24216826

[9] Tennler, J., Raeder, C., Praetorius, A., Ohmann, T., & Schoepp, C. (2023). Effectiveness of the SMART training intervention on ankle joint function in patients with first-time acute lateral ankle sprain: Study protocol for a randomized controlled trial. *Trials, 24*(1), 162. https://doi.org/10.1186/s13063-023-07195-2

[10] Mousavi, S. H., Khorramroo, F., Minoonejad, H., & Zwerver, J. (2023). Effects of biofeedback on biomechanical factors associated with chronic ankle instability: A systematic review with meta-analysis. *BMC Sports Science, Medicine & Rehabilitation, 15*(1), 168. https://doi.org/10.1186/s13102-023-00780-7

[11] Latif, A., Al Janabi, H. F., Joshi, M., Fusari, G., Shepherd, L., Darzi, A., & Leff, D. R. (2024). Use of commercially available wearable devices for physical rehabilitation in healthcare: a systematic review. *BMJ Open, 14*(11), e084086. https://doi.org/10.1136/bmjopen-2024-084086

[12] Yona, T., Peskin, B., & Fischer, A. (2024). Stepping it up: a longitudinal assessment of stair negotiation among ACL reconstruction patients outside the laboratory. *medRxiv*. https://doi.org/10.1101/2024.05.16.24307484

[13] Van Hooren, B., Plasqui, G., & Meijer, K. (2024). The effect of wearable-based real-time feedback on running injuries and running performance: a randomized controlled trial. *The American Journal of Sports Medicine, 52*(3), 750–765. https://doi.org/10.1177/03635465231222464

[14] Feng, Y., Liu, Y., Fang, Y., Chang, J., Deng, F., Liu, J., & Xiong, Y. (2023). Advances in the application of wearable sensors for gait analysis after total knee arthroplasty: a systematic review. *Arthroplasty (London, England), 5*(1), 49. https://doi.org/10.1186/s42836-023-00204-4

[15] Dobson, R., Stowell, M., Warren, J., Tane, T., Ni, L., Gu, Y., McCool, J., & Whittaker, R. (2023). Use of consumer wearables in health research: issues and considerations. *Journal of Medical Internet Research, 25*, e52444. https://doi.org/10.2196/52444

[16] Wei, S., & Wu, Z. (2023). The application of wearable sensors and machine learning algorithms in rehabilitation training: A systematic review. *Sensors (Basel, Switzerland), 23*(18), 7667. https://doi.org/10.3390/s23187667

[17] Chikwetu, L., Miao, Y., Woldetensae, M. K., Bell, D., Goldenholz, D. M., & Dunn, J. (2023). Does deidentification of data from wearable devices give us a false sense of security? A systematic review. *The Lancet. Digital Health, 5*(4), e239–e247. https://doi.org/10.1016/S2589-7500(22)00234-5

[18] Katmah, R., Shehhi, A. A., Jelinek, H. F., Hulleck, A. A., & Khalaf, K. (2023). A systematic review of gait analysis in the context of multimodal sensing fusion and AI. *IEEE Transactions on Neural Systems and Rehabilitation Engineering: A Publication of the IEEE Engineering in Medicine and Biology Society, 31*, 4189–4202. https://doi.org/10.1109/TNSRE.2023.3325215

DOI: 10.54254/2753-8818/2026.37986

[19] Miller, A. E., Lohse, K. R., Bland, M. D., Konrad, J. D., Hoyt, C. R., Lenze, E. J., & Lang, C. E. (2024). A large harmonized upper and lower limb accelerometry dataset: A resource for rehabilitation scientists. *medRxiv: The Preprint Server for Health Sciences*, 2024.08.15.24312066. https://doi.org/10.1101/2024.08.15.24312066

[20] Forsyth, L., Ligeti, A., Blyth, M., Clarke, J. V., & Riches, P. E. (2024). Validity of wearable sensors for total knee arthroplasty (TKA) rehabilitation: A study in younger and older healthy participants. *The Knee, 51*, 292–302. https://doi.org/10.1016/j.knee.2024.10.006