

# Wearable- and Sensor-Based Artificial Intelligence in Exercise Science: IMUs, Heart-Rate Variability, and EMG for Real-Time Coaching and Fatigue/Recovery Prediction

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## ABSTRACT

**Introduction and Objective.** Wearable sensors and artificial intelligence (AI) are increasingly being used to monitor human movement, physiological responses, fatigue and recovery during exercise. Inertial measurement units (IMUs), heart-rate variability (HRV) and surface electromyography (sEMG) provide complementary information about movement, autonomic regulation and neuromuscular activity. This narrative review examines how machine-learning (ML) methods can integrate these signals to support real-time coaching, fatigue monitoring and recovery prediction. **Material and method.** The review considered applications involving wearable movement sensors, cardiovascular monitoring, EMG, training-load variables and individualized physiological responses. Particular attention was given to signal preprocessing, feature extraction, multimodal data fusion, temporal modelling, individualized baselines and real-time decision support. **Results.** IMU-based systems can identify movement patterns and changes in exercise technique, while HRV provides longitudinal information related to cardiovascular and autonomic responses. EMG can contribute information about muscle activation and neuromuscular fatigue. ML can combine these heterogeneous signals to estimate exercise intensity, detect changes in movement or fatigue, and support individualized recovery assessment. However, performance varies according to sensor quality, population characteristics, experimental conditions and validation strategy. Motion artifacts, individual variability, limited external validation, laboratory-to-field differences and model interpretability remain important limitations. **Conclusions.** Wearable AI represents a promising decision-support technology for exercise science, particularly when multiple sensor modalities are integrated longitudinally. Current evidence supports its use for monitoring and individualized feedback rather than autonomous high-stakes decision-making. Future research should prioritize multimodal validation, real-world longitudinal studies, transparent algorithms and integration with professional coaching and clinical expertise.

**Keywords:** wearable technology, artificial intelligence, machine learning, inertial measurement unit, heart-rate variability

## INTRODUCTION

Wearable technology has changed the way exercise and physiological responses can be monitored outside traditional laboratory environments. Conventional exercise assessment often relies on periodic testing, laboratory equipment and subjective observation. Although these approaches remain important, they provide limited information about how an individual's movement and physiological responses change continuously throughout exercise and across successive training sessions.

Wearable sensors provide an opportunity to collect repeated measurements under relatively natural conditions. IMUs can characterize acceleration, angular velocity and body movement; heart-rate sensors can provide information about cardiovascular responses; and sEMG can describe patterns of muscle activation. When these signals are analyzed using ML, the resulting systems can identify multidimensional patterns that may not be apparent from individual measurements [1-5].

The development of wearable AI has therefore shifted the focus from simply collecting exercise data toward interpreting these data in real time. A wearable system could potentially detect changes in movement mechanics, identify an increasing physiological response or estimate fatigue progression and then provide

feedback to an athlete or exercise professional. This creates a feedback loop in which sensing, computational analysis and exercise decision support occur within the same monitoring framework.

Wearable AI is particularly relevant to exercise science because fatigue and recovery are dynamic processes. The same exercise workload may produce different responses depending on training status, sleep, previous workload, environmental conditions and individual characteristics. Consequently, fixed population-level thresholds may not adequately represent an individual's response. Longitudinal ML models may provide an alternative by evaluating current measurements relative to the individual's previous observations [1,2].

The purpose of this review is to examine the application of wearable and sensor-based AI in exercise science, with particular emphasis on IMUs, HRV and EMG. The review focuses on their roles in movement monitoring, fatigue detection, recovery prediction, real-time coaching and multimodal decision support.

## **MATERIAL AND METHOD**

**Review design.** A narrative review approach was used to integrate literature addressing wearable sensors, artificial intelligence, machine learning, exercise monitoring, fatigue, recovery and rehabilitation. The analytical framework was organized around sensor acquisition, signal processing, feature extraction, ML modelling, prediction and practical decision support.

**Sensor domains.** Three principal sensor domains were considered. The first was IMU-based movement monitoring, including acceleration, angular velocity, orientation and movement variability. The second was cardiovascular monitoring, particularly HRV and heart-rate measurements. The third was sEMG-based assessment of muscle activation and neuromuscular fatigue. Training load, sleep and subjective measures were considered as complementary variables.

**Signal preprocessing.** Wearable signals require appropriate preprocessing before ML analysis. Common procedures include filtering, artifact detection, segmentation, normalization and synchronization between different sensors. IMU signals can be affected by sensor displacement and movement artifacts, while sEMG is sensitive to electrode placement, skin conditions and signal noise. Cardiac measurements may also be affected by motion and measurement conditions. Poor preprocessing can therefore reduce the validity of subsequent predictions [2,3].

**Feature construction.** Features may be derived from time-domain, frequency-domain or temporal characteristics. IMU features can include acceleration magnitude, movement range, peak acceleration, angular velocity and movement variability. HRV features may include RMSSD and other time- or frequency-domain measures. EMG features can include amplitude, frequency characteristics and changes in muscle activation patterns. These variables can be combined with training load, sleep and perceived exertion to provide contextual information.

**Machine-learning approaches.** Potential approaches include logistic regression, regularized regression, support vector machines, random forests, gradient-boosting methods and neural networks. Sequence-based models may be useful when fatigue and recovery depend on the temporal history of previous exercise sessions. More complex models should nevertheless be justified by dataset size and validated against simpler baseline approaches.

**Validation principles.** Validation should reflect the intended application. If the model is intended to generalize to new individuals, participant-level splitting is required. If the model is designed to predict future responses within an existing individual, temporal validation is more appropriate. Randomly splitting repeated measurements from the same participant can result in information leakage and overly optimistic estimates of performance.

## RESULTS

### **IMU-Based Movement Monitoring**

IMUs are among the most practical wearable sensors for monitoring human movement. They are relatively small, portable and capable of collecting high-frequency data during walking, running, jumping, resistance exercise and sport-specific activities.

Machine-learning models can transform IMU signals into information about movement classification, exercise technique and changes in mechanical behavior. For example, acceleration and angular-velocity patterns can be used to distinguish exercise movements or identify changes in movement execution. Longitudinal measurements can additionally be used to establish an individual's normal movement pattern and identify deviations from baseline [2,3].

Fatigue monitoring is a particularly relevant application. As fatigue develops, athletes may modify movement strategies, coordination or movement consistency. An IMU-based system can potentially detect these changes continuously without requiring laboratory-based motion capture. However, a detected change does not necessarily indicate physiological fatigue because sensor displacement, technical execution and environmental conditions can produce similar changes.

### **Heart-Rate Variability and Physiological Monitoring**

HRV provides information about variation in the intervals between successive heartbeats and is frequently investigated in relation to autonomic regulation, training stress and recovery. Unlike average heart rate, HRV can provide information about changes in cardiac timing and may therefore contribute to longitudinal monitoring.

Wearable devices allow cardiac measurements to be collected repeatedly, creating opportunities for ML models to evaluate HRV relative to an individual's baseline. A model could combine HRV with resting heart rate, recent training load, sleep, exercise performance and perceived recovery to estimate whether the current response differs from the individual's usual pattern.

However, HRV should not be interpreted as a universal or independent measure of recovery. It can be influenced by sleep, stress, illness, breathing, measurement conditions and other factors. ML systems using HRV should therefore consider longitudinal trends and contextual variables rather than relying on a single threshold.

### **EMG and Neuromuscular Fatigue**

Surface EMG provides information about electrical activity associated with muscle activation and therefore offers a complementary perspective to movement sensors. During prolonged or repeated exercise, changes in EMG amplitude, frequency characteristics or muscle-recruitment patterns may accompany neuromuscular fatigue.

The combination of EMG and IMU data is particularly relevant because the two modalities measure different aspects of exercise. IMUs describe external movement, whereas EMG provides information about muscular activation. An athlete may maintain a similar movement pattern while changing muscle recruitment as fatigue develops. Multimodal ML may therefore identify fatigue-related patterns that would be difficult to detect using either sensor alone.

The practical limitation is that EMG is sensitive to electrode position, skin preparation, muscle geometry and movement artifact. These factors must be controlled carefully when models are intended for longitudinal use.

### **Multimodal Machine Learning**

The major opportunity for wearable AI lies in combining multiple sensor streams. A multimodal system may integrate:

| Data source   | Example information                      | Potential role                      |
|---------------|------------------------------------------|-------------------------------------|
| IMU           | Acceleration, angular velocity, movement | Movement and mechanical response    |
| HR/HRV        | Heart rate, RMSSD, cardiac variability   | Physiological and recovery response |
| sEMG          | Amplitude, frequency, activation pattern | Neuromuscular fatigue               |
| Sleep         | Duration, quality, disruption            | Recovery context                    |
| Training load | Duration, intensity, volume              | Training exposure                   |
| RPE           | Perceived exertion, fatigue              | Subjective response                 |
| Performance   | Velocity, power, repetitions             | Functional response                 |

These signals can be integrated using a pipeline such as:

**Wearable sensors → preprocessing → feature extraction → ML model → fatigue/recovery estimation → feedback → updated sensor data**

The advantage of multimodal modelling is that physiological and mechanical responses can be interpreted together. For example, a reduction in movement velocity accompanied by altered EMG characteristics and an elevated physiological response may provide a different interpretation from a movement change occurring without any physiological deviation.

### **Real-Time Coaching**

Real-time coaching represents one of the most practical applications of wearable AI. During exercise, a model may analyze movement and physiological data continuously and provide feedback concerning exercise intensity, movement quality, recovery interval or technique.

For resistance exercise, IMUs can potentially identify movement velocity and repetition characteristics, while EMG provides information about muscle activation. Heart rate and perceived exertion can provide

additional context. A system could then identify an unusual response and generate a recommendation for further assessment or adjustment.

However, real-time prediction should not automatically be translated into autonomous training modification. The same sensor pattern may have different meanings depending on exercise type, training history, competition schedule, sleep, nutrition or health status. Professional interpretation remains important, particularly when recommendations could affect safety or rehabilitation.

### **Fatigue Prediction**

Fatigue prediction differs from simple fatigue measurement because the model attempts to estimate a future or developing state. Wearable AI can potentially combine recent training exposure with changes in movement, cardiovascular response and neuromuscular activity.

Temporal models are particularly relevant because fatigue may develop progressively. A single abnormal measurement may be less informative than a consistent trend across several sessions. Models can therefore use rolling features, individual baselines and sequential observations to distinguish isolated variation from persistent changes.

Nevertheless, fatigue itself is multidimensional. Perceived fatigue, neuromuscular fatigue, cardiovascular strain and performance decline do not necessarily occur simultaneously. Consequently, a model should clearly specify which fatigue-related outcome it predicts rather than treating fatigue as a single universal physiological state.

### **Recovery Prediction**

Recovery prediction provides a complementary application of wearable AI. Potential predictors include HRV, resting heart rate, sleep, previous training load, movement characteristics, exercise performance and subjective recovery.

Individualized baselines are particularly important. A particular HRV value or movement characteristic may be normal for one person but unusual for another. ML systems can potentially learn these individual patterns over time and identify deviations relative to personal history.

The output should nevertheless be interpreted as an estimate rather than a direct measurement of recovery. A practical system should provide uncertainty and allow coaches or clinicians to consider additional information before changing training.

### **Closed-Loop Exercise Systems**

The most advanced concept is a closed-loop system in which sensing, prediction and feedback are continuously connected:

**Sensing → Processing → Prediction → Decision support → Feedback → New sensing**

Such systems could potentially provide visual, auditory, haptic or coach-mediated feedback during exercise. The concept is particularly attractive for rehabilitation and individualized training because the system can continuously evaluate whether the exercise response is consistent with the expected pattern.

At present, however, fully autonomous closed-loop exercise prescription remains an emerging research concept. Most existing systems are better characterized as monitoring and decision-support technologies rather than independently validated training-control systems.

## **DISCUSSION**

The principal finding of this review is that wearable AI can combine movement and physiological signals to provide more continuous information about exercise response. IMUs, HRV and EMG each provide different information, and their combination may be more informative than isolated measurements.

The major methodological challenge is **individual variability**. Exercise responses differ substantially between individuals, and a model developed from one population may not generalize to another.

Participant-level validation and external testing are therefore essential when assessing whether a wearable AI system can be applied beyond its original dataset.

A second challenge is **laboratory-to-field translation**. Controlled experiments allow researchers to standardize exercise intensity and sensor placement, but real-world exercise contains substantially more variability. Devices may move, sensors may lose signal quality, environmental conditions may change and athletes may perform movements that were not included in the training dataset.

A third issue concerns **multimodal data synchronization**. IMU, HRV and EMG signals operate at different sampling frequencies and respond on different time scales. Combining these signals therefore requires appropriate temporal alignment and preprocessing. Poor synchronization can create artificial relationships that an ML model may incorrectly interpret as meaningful.

**Explainability** is also important. Coaches and clinicians may need to understand why a system identifies an athlete as fatigued or recommends additional recovery. Feature-importance methods can help identify influential variables, but predictive contribution should not be interpreted as proof of causality.

Another important consideration is **data quality**. More sensors do not necessarily produce better predictions. If one signal contains substantial noise or systematic measurement error, adding it to a multimodal model may reduce rather than improve generalization. Quality control should therefore be considered an essential part of the wearable AI pipeline.

From a practical perspective, wearable AI is most appropriately viewed as **decision support**. The technology can provide continuous information that would be difficult for a coach or clinician to collect manually, while professional expertise remains necessary for contextual interpretation. This approach also reduces the risk of treating a statistical prediction as a definitive physiological diagnosis.

### **Future Research Directions**

Future studies should prioritize multimodal and longitudinal datasets that combine IMU, HRV, EMG, training load, sleep and subjective responses. Models should be evaluated across different populations, sports and real-world environments rather than only under controlled laboratory conditions.

Research should also compare complex ML models with transparent statistical baselines. A more sophisticated algorithm should demonstrate reproducible improvement in out-of-sample performance before being adopted in practice.

Finally, future systems should emphasize human-centered explainability. Rather than producing only a binary “train” or “rest” output, wearable AI should communicate the major factors contributing to a prediction and indicate the uncertainty surrounding the estimate.

## **CONCLUSIONS**

Wearable- and sensor-based AI provides a promising framework for continuous exercise monitoring, fatigue assessment and recovery prediction. IMUs provide information about movement and mechanical behavior, HRV contributes information about cardiovascular and autonomic responses, and EMG provides complementary information about muscle activation and neuromuscular changes.

The principal value of wearable AI lies in integrating these signals over time and translating large volumes of sensor data into interpretable decision support. Multimodal systems may allow exercise professionals to identify changes in movement, physiological response and fatigue earlier than would be possible through isolated measurements.

However, sensor noise, individual variability, laboratory-to-field differences, limited external validation, explainability and data privacy remain important challenges. Current evidence therefore supports wearable AI primarily as a technology that **augments professional coaching and exercise-science expertise rather than replacing it**.

Future development should focus on multimodal sensing, individualized longitudinal modelling, real-world validation and human-AI collaboration. These advances may enable exercise monitoring and coaching to become increasingly continuous, personalized and responsive to changes in training and recovery.

## REFERENCES

1. Jiang Y, Malliaras P, Chen B, Kulić D. Real-time forecasting of exercise-induced fatigue from wearable sensors. *Comput Biol Med.* 2022;148:105905. <https://doi.org/10.1016/j.compbimed.2022.105905>
2. Madrigal-Cerezo R, Domínguez-Sanz N, Martín-Rodríguez A. Wearable biosensing and machine learning for data-driven training and coaching support. *Biosensors.* 2026;16(2):97. <https://doi.org/10.3390/bios16020097>
3. Wei S, Wu Z. The application of wearable sensors and machine learning algorithms in rehabilitation training: a systematic review. *Sensors.* 2023;23(18):7667. <https://doi.org/10.3390/s23187667>
4. Reiner SL, Pearson RC, Reed RA, Olenick AA, Pojednic RM. Artificial intelligence in exercise programming and coaching: opportunities and limitations. *Curr Sports Med Rep.* 2026;25(8):245-252. <https://doi.org/10.1249/JSR.0000000000001357>
5. Fatigue Monitoring Through Wearables: A State-of-the-Art Review. *Sensors.* 2022.
6. Seshadri DR, Li RT, Voos JE, et al. Wearable sensors for monitoring the physiological and biochemical profile of the athlete. *NPJ Digit Med.* 2019;2:72. <https://doi.org/10.1038/s41746-019-0150-9>
7. Halson SL. Monitoring training load to understand fatigue in athletes. *Sports Med.* 2014;44(Suppl 2):S139-S147. <https://doi.org/10.1007/s40279-014-0253-z>
8. The impact of machine learning on physical activity-related health outcomes: a systematic review and meta-analysis. *PubMed.* 2025.
9. Using artificial intelligence for exercise prescription in personalised health promotion: a critical evaluation of OpenAI's GPT-4 model. *BMC Sports Sci Med Rehabil.* 2024.
10. Abruñedo-Lombardero J, Padrón-Cabo A, Vélez-Serrano D, Álvaro-Meca A, Iglesias-Soler E. An explainable machine learning approach to explain the effects of training and match load on ultra-short-term heart rate variability in semi-professional basketball players. *Sensors.* 2025;25(22):6928. <https://doi.org/10.3390/s25226928>
11. Bartlett R, Wheat J, Robins M. Is movement variability important for sports biomechanists? *Sports Biomech.* 2007;6(2):224-243. <https://doi.org/10.1080/14763140701322994>
12. Varcin F, Boocock MG. The accuracy, validity and reliability of Theia3D markerless motion capture for studying the biomechanics of human movement: a systematic review. *Artificial Intelligence in Medicine.* 2026;173:103332. doi:10.1016/j.artmed.2025.103332.