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# Discussion on the Practical Role of Wearable Devices in Human Body Tracking, Enhancement of Exercise Efficiency, and Protection against Sports Injuries

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**Abstract:** Wearable devices have evolved from simple step counters to multi-sensor monitoring systems. The world's market for wearable technology will be about 86.78 billion US dollars by 2025. The amount of money for the market of smart sports wearable devices in China has risen from 2.165 billion yuan in 2019 to 5.447 billion yuan in 2024. Human motion tracking, improvement of exercise efficiency and sports injury prevention are the contents of this paper; at the same time, it studies the application value of wearable devices in sports training. The Inertial Measurement Unit estimates gait parameters that are highly consistent with laboratory equipment; the correlation coefficient for joint angle prediction is between 0.93 and 0.99, and the average absolute percentage error of heart rate monitoring by smartwatches is less than the 10% validity threshold; the machine learning model based on wearable sensor data predicts the risk of subacromial impingement syndrome with an accuracy of 85% to 88%. The energy-consumption estimates for most of the devices are not in line with the gold standard. Collect the relevant empirical data, determine the technical limits of all types of devices, and provide a reference for selecting wearable devices in sports training.

**Keywords:** Wearable devices, Motion tracking, Motion efficiency, Injury protection, Biomechanical monitoring.

## 1. Introduction

In recent years, wearable devices for sports and health applications have been developing at a high speed. According to industry statistics, by 2025, the size of the world market for wearable technology will be about 86.78 billion US dollars, and by 2034, it is expected to reach around 231.43 billion US dollars. According to data published by LeadLeo Research Institute, the scale of the domestic market for smart sports wearable devices has been on the rise; in 2019, it was approximately 2.165 billion yuan, and by 2024, it has reached around 5.447 billion yuan, with a high annual growth rate of about 19.04 per cent. It is expected that from 2025 to 2029, it will increase from 5.924 billion yuan to 8.627 billion yuan. On the one hand, people are becoming more and more health-conscious nowadays. At the same time, wearable devices are also changing from general consumer electronics into specific sports-training aids.

Wearable devices can be widely used in training, and these devices help address some deficiencies of the old-style observation method. Although three-dimensional motion-capture systems and force platforms are highly accurate lab instruments, they are relatively expensive and have high-specification venues. They are not suitable for general-purpose use or outdoor work. Only based on observation and experience did the coaches know the physical condition of the athletes during training, and real-time, objective data support was unavailable at that time. Wearable devices are relatively small in size and have a lower cost.

Currently, the wearable devices for sports can be generally divided into three categories: smartwatches and smart bands are used for monitoring cardiovascular physiological indicators; inertial measurement unit-based devices gather biomechanical data; and others integrate multiple sensors into textiles or patches. The indicators collected by them include heart rate, heart rate variability, step frequency, stride length, landing time and vertical amplitude, among others. However, the actual tracking accuracy and how much improved sports efficiency will be achieved by these devices are unknown, and whether they can truly help prevent injuries also needs to be verified through experiments. Based on the above three directions, this paper uses existing research results to provide an initial assessment of the real-life applications of wearable devices [1].

## 2. Technical Principles and Accuracy Verification of Wearable Devices in Human Motion Tracking

Miniature Sensors are used for human motion tracking. The above four are typical examples of accelerometers, gyroscopes, magnetometers and photoplethysmogram sensors. These devices are worn by people to collect various physical data that changes with their movement and save this information [2]. The three parts inside the Inertial Measurement Unit are an accelerometer, a gyroscope, and these are generally referred to as Inertial Measurement Units. Micro-electromechanical system (MEMS) technology has developed rapidly in recent years, and with a reduction in sensor size and cost, more wearable devices are now being deployed widely.

Some earlier studies have verified the accuracy of gait parameter measurement. Some scholars have employed wearable motion sensors to predict the kinematic parameters of lower-limb joints in the sagittal plane. Based on the above results, the range of the correlation coefficient was 0.93 - 0.99, and the average absolute deviation did not exceed 2.3. Another study focused on a high-intensity running case. The Researchers used inertial measurement units to determine the step time and compared it with that of the reference system. The results show that the mean difference of the two is 0 $\pm$ 6 ms and the correlation coefficient is 0.97. According to the above data, wearable devices have reached a certain level in the measurement of gait-phase parameters and are close to those of laboratory equipment.

Attention to the accuracy of heart-rate measurement in the field of cardiopulmonary function has gradually begun to increase. A total of 56 studies were carried out to evaluate the accuracy of heart rate, energy consumption and step counting by an Apple Watch. The analysis shows that the mean absolute percentage error of heart rate measurement is 4.43% and is below the 10% validity threshold. Therefore, it can be known that smartwatches are feasible for this purpose.

Wearable devices have different performances in various areas. According to the above analysis, the average absolute percentage error in the energy consumption estimation is 27.96%, far exceeding the 10% limit. Other validation studies have reached the same conclusion and indicated that the agreement between wrist-worn devices' measurement of energy consumption and the gold standard is relatively small. Therefore, when using these devices, one should be aware of the accuracy limitations in the various indicators of these devices. The above estimated indicators of energy consumption should not be trusted too much.

The effects of the accuracy difference are not the same in different sports. Periodic events, such as running, have relatively stable basic parameters of heart rate and step frequency, and the data obtained by devices are relatively high in the reference value. Ball games and other types of competitions generally have a large number of movement patterns and distances, and interference from signals is more likely to occur; therefore, the error rate is relatively high. Evaluate the reliability of the data during tracking based on the nature of the event [3].

# 3. The Mechanism and Empirical Basis of the Effect of Wearable Devices on Improving Sports Efficiency

Recently, many people have been discussing whether wearable devices can improve the efficacy and scientific basis of exercise training. Based on the above accuracy data, it can be determined that the devices are capable of collecting some information; however, measuring and applying this data effectively are separate issues. The three contents of this discussion are as follows. Numerically mark the training load, set up different plans for different people, and provide real-time feedback on technical movements during exercise.

First, we will set the quantity of training. In the past, coaches mainly used their own experience, and athletes would only report how tired they were or how they felt after training; thus, the evaluation was based on these limited reports and relatively prone to error. The device will be worn to obtain real-time data on heart rate, heart rate variability and acceleration, and a specific number of training intensity will be calculated. Based on the above data, the coach will determine whether the current amount is reasonable or if it needs to be changed. Some scholars have shown that wearable monitoring technology can quantify the training process and help us learn how a person's body reacts to changes in training load [4].

Personalised training also has some specific features. The same training plan will have different effects on different people. Some will recover relatively quickly; others may still be in a bad way the next day. Over a long period of time, wearable devices can learn individual differences and track various patterns, such as how quickly a person's heart rate returns to normal after exercise, their heart rate during sleep, and the duration of sleep each night. Based on the above data, the coach will know how strenuous the exercise is at a particular time. They will be chosen more often.

The first kind of real-time feedback for wearable devices will likely be implemented first. In the past, changes to the training plan were often communicated by shouting or showing videos, and the feedback loop was slow; thus, the pace of training could be disrupted. Now, these devices can display the number of steps taken, landing time and vertical amplitude during exercise, and athletes can adjust on the spot. A study used the built-in voice notification function of a smartwatch to have runners increase their step frequency by 10%, and thus moved the previously only achievable gait training in a laboratory to outdoor running tracks. Thus, the knee pain of female runners has been reduced and the function of their knees has improved. The researchers speculated that it might be that the change in step frequency reduced the angle of knee flexion and thus slightly lowered the ground impact force [5].

Not only for professional athletes. Regular runners, fitness enthusiasts and people in physical therapy training can all be helped by this. Immediately inform the child of any errors in their direction of movement so they can learn to move more efficiently and safely.

# 4. Application Path and Effect Evaluation of Wearable Devices in Sports Injury Prevention

Wearable devices have been applying to help prevent sports injuries recently and have attracted considerable interest in the field of sports injury prevention. The logical chain is as follows: Continuously monitor the body's function and movement of the athlete's body; systemically recognize early warning signs of injury; issue a warning; and then guide other measures. The three links of monitoring, warning and response form a closed loop.

A worn-wearable device will be able to collect these data at a certain time. Muscle fatigue is often due to the exercise that has taken place. Some scholars have proposed that, at present, research on using wearable devices to detect and forecast muscle fatigue during exercise is being carried out in an integrated manner by rehabilitation medicine and sports science. Slightly stronger muscles in a certain area of the body have a low fatigue level during activity according to surface electromyography (sEMG). Another way is that some scholars have proposed a fatigue detection framework based on inertial sensors and heart-rate signals to calculate a light-weight physiological fatigue index that is suitable for real-time operation on the device side [6].

Machine learning algorithms can be used to enhance the prediction performance of the warning system at the beginning of an incident. In 2025, Scientific Reports released a paper in a journal on preventing subacromial impingement syndrome. Fifty people were recruited as the subjects and worn on-body gyroscopes and accelerometers were used to collect shoulder movement data. Based on the above data, the range of movement for repeated overhead exercises by the patient is relatively small compared to that of a healthy person. Based on the above data, the machine learning model trained reached an accuracy of 85%-88% in predicting the risk of impact. The study has also introduced a real-time feedback mechanism and actively guided the movement. Therefore, the purpose of wearble devices has expanded beyond merely data collection to risk anticipation.

At the intervention level, the new real-time data can be used to adjust the training plan for coaches and athletes quickly. A higher heart rate indicates that one is more fatigued or hurt and may occur earlier. Wearable devices are also being used in the military training area to monitor training load, prevent injuries and detect fatigue [7].

The two types of injuries to be prevented are sudden ones and wear and tear over time. Continually collect data on how much exercise athletes have been doing and observe any problems in their bodies to find out about overtraining sooner so that adjustments can be made to their exercise plan. The implementation of the above protective effects relies on the reliability of data provided by equipment, and thus, an inherent limitation in the current wearable devices is their lack of precision.

# 5. Analysis of Factors Affecting the Accuracy of Wearable Devices' Data and Their Limitations

There are several reasons for the inaccuracies in data from wearable devices. Various factors will lead to differences in the measured results: the type of device, where it is worn, how often and in what way exercise is performed, and individual differences in physical fitness are all reasons.

The overall error of the heart-rate monitoring is relatively small, but this is not the case in an exercise scenario. For activities with a large amplitude of arm swing, the optical heart-rate sensor also moves with it, and the data may be inaccurate. Smartwatches by different brands and models have varying results. A systematic review of the 65 studies included found that the mean absolute percentage error of heart rate measurement by Apple Watch was less than 10 per cent. The Hong Kong Consumer Council also conducted a test and evaluation of 44 products (Issue 583 of "Choice") - the Apple Watch Series 9 had a heart-rate deviation of no more than 2% in various states such as rest, walking, running and cycling. However, the Amazfit GTS 4 Mini had a heart-rate deviation of up to 22 per cent during exercise [8].

Estimation of the energy-consumption problem is relatively severe. There is another set of data in the same systematic review, and the average absolute percentage error in energy consumption is more than 30 per cent. All of the tested brands were damaged. In short, based on the above analysis, none of the energy consumption data from the devices were reliable. Energy-consumption data for wrist-worn devices are considerably different from the gold standard of indirect calorimetry. Based on the long-term trend, it is feasible; however, it is not highly precise and thus less reliable for actual application.

Gait analysis has a different kind of problem. The Location of the Sensor will affect the measured data to some extent. Some research has compared commercial smartwatches and ankle-mounted inertial measurement units to find that the two are not easily interchangeable. Different positions at the wrist, waist and lower back, and on the feet are all different kinds of kinematic data. They are used to measure different things in different ways.

In short, the data obtained by wearable devices have not yet been corroborated by clinical or laboratory studies. It is very suitable for training in a field to observe changes and issue an early warning. However, it is far from being able to replace professional diagnostic equipment. Users need to have a sense of proportion and know which indicators the device is reasonably trustworthy with, and which are probably inaccurate. Heart-rate monitoring is influenced by motion artifacts and requires optimised hardware design and algorithm filtering; energy consumption cannot be accurately determined because the information dimension of the wrist-worn device is insufficient, and multi-source data fusion must be employed; gait analysis is sensitive to sensor position, so flexible patches and smart clothing have precisely solved the problem of a fixed position [9].

# 6. The Development Trends and Practical Suggestions of Wearable Devices in Sports Science

The future development direction of wearable devices for sports science is worth studying in a few places. Changes in technology and changes in the demand for training are also reasons for this change.

Many sensors and artificial intelligence algorithms have been integrated recently to some extent. Accelerometers, gyroscopes, heart-rate sensors and electromyography sensors are all new hardware that has been combined. After being processed by machine learning, the device will no longer display just one kind of health data, such as heart rate or step count, but will offer all-encompassing health data for the athlete. Some research has already started to use data from multiple wearable sensors for the early warning of sports injuries. Energy consumption estimation is a typical case; therefore, using only the photoplethysmographic pulse-wave signal from a wrist-worn device has consistently resulted in relatively large estimation errors. By adding the body-activity-intensity data from an accelerometer, the cardiopulmonary-load index derived from a heart-rate sensor, and the user's basic-metabolic-parameters to this framework, machine-learning-based multimodal fusion can be applied to enhance the individualisation accuracy of the energy-consumption model [10].

The Shapes of the Devices are also changing. Watches were the most popular before. With the development of flexible electronics and new materials, smart clothing and patch-type devices have recently entered the market. A sensor has been embedded in the clothing to improve the fit and wearing experience of life-saving equipment. The Stability of signal collection has also improved. They are more comfortable to wear now, so the athletes have been wearing them for an extended period and have collected more data. The integration of wearable devices and the body will continue to deepen, and the quality of the data will also be high.

The position of the function will also change. Devices record data and, at the same time, extend to include analysis and recommendations. Record, analyze, offer suggestions, and so on, and then complete a typical service cycle. Some specific cases and their corresponding applications are as follows.

First, the wearable devices for the training are only auxiliary tools. Coaches and athletes need to know which indices of this device are reliable and which are prone to errors. Values such as energy consumption and maximum oxygen uptake are calculated estimates; only a general trend needs to be observed, and they are not precise enough to be used as such [11].

Secondly, a particular type of device and a specific place for wearing it must be selected based on the purpose of the training and the features of the training project. Running is a typical case. An inertial measurement unit will be used to obtain walking data, and a heart-rate sensor will not be used.

Thirdly, in presenting the results of data analysis, a larger scope of changes should also be displayed. Tracking the long-term changes of the same object is generally more meaningful than comparing different individuals.

Fourthly, the data security and privacy protection of this project need to be guaranteed. The more devices that are worn, the more detailed the physiological data collected will be. There are always certain problems concerning the personal data of athletes in training.

# 7. Conclusion

Based on the discussions in the above sections, the following points can be drawn from the perspectives of human tracking, improvement of movement efficiency and injury prevention.

First, we will address human tracking. Wearable devices are already relatively accurate in some of the above indicators. The correlation coefficient between the prediction of joint angles by the inertial measurement unit and that of the reference system in gait analysis is between 0.93 and 0.99. Multiple studies have found that the average absolute percentage error of commercial smartwatches in heart-rate monitoring is less than 10 per cent and thus meets the validity requirement. The two kinds of data show that wearable devices are feasible for monitoring cardiopulmonary function and some basic kinematic parameters. The accuracy of the calculation indicators for energy consumption has not risen significantly, and precise measurement is unfeasible.

Second, to enhance the efficiency of exercise. Wearable devices have been using three kinds of functions for some time to track exercise load, customize training plans, and give prompt feedback on exercise posture. Coaches adjust their plans according to real-time data, and smartwatches can issue sound cues to guide step-frequency training for runners to enhance the knee-joint function of the knees. However, the research observation period is relatively short now, and the long-term effects have not been verified by follow-up studies.

Thirdly, there is the problem of injury. Wearable devices are moving from "data collection" to "risk alerts". The accuracy rates of the prediction of subacromial impingement syndrome for the two machines in the machine learning experiment reached 85% and 88%, respectively; these are considered relatively good results. However, injuries have many reasons, and the device can only obtain some signals; therefore, it cannot replace professional medical examination and all-around protective measures.

Most studies have shown that wearable devices are feasible in practice for all of the above areas, but there are also limitations to their functions. There are noticeable differences in the precision indices, and the calculated indicators of energy consumption need to be handled carefully. When used as a training aid, one must be aware of its limits in accuracy and circumstances under which it is suitable for application.

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