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Real Time Monitoring Research on Rehabilitation Effect of Artificial Intelligence Wearable Equipment on Track and Field Athletes

Bin Wu[1,*]

[1]School of Physical Education, Shandong Women's University, Jinan 250300, Shandong, China

Abstract

INTRODUCTION: With the rapid development of artificial intelligence technology, wearable artificial intelligence devices show great potential in medical rehabilitation. This study explores the Real Time monitoring effect of AI wearable devices in the rehabilitation process of track and field athletes. The application of this technology in rehabilitation monitoring was investigated through the introduction of advanced sensing technology and data analysis algorithms to provide track and field athletes with more scientific and personalized rehabilitation programs.
OBJECTIVE: A group of track and field athletes was selected as the research object and equipped with an artificial intelligence wearable device, which is capable of Real Time monitoring of the athletes' physiological parameters, sports postures, joint mobility, and other rehabilitation-related data. An individualized rehabilitation model was established through the data collected by these sensors, and advanced artificial intelligence algorithms were used to analyze the data in Real Time. At the same time, the sensor data were combined with the actual performance of the athletes' rehabilitation training to comprehensively assess the effectiveness of AI wearable devices in rehabilitation monitoring.
METHODS: This study aims to assess the effect of Real Time monitoring of AI wearable devices in the rehabilitation of track and field athletes and to explore their potential application in the rehabilitation process. Real Time tracking of athletes' physiological status and athletic performance aims to provide more accurate and timely information to rehabilitation doctors and coaches to optimize the rehabilitation training program and promote the rehabilitation process of athletes.
RESULTS: The study showed that artificial intelligence wearable devices have significant Real Time monitoring effects in rehabilitating track and field athletes. Through Real Time monitoring of data such as physiological parameters, sports posture, and joint mobility, the rehabilitation team was able to identify potential problems and adjust the rehabilitation program in a more timely manner. Athletes using artificial intelligence wearable devices improved the personalization and targeting of rehabilitation training, and the rehabilitation effect was significantly better than that of traditional monitoring methods.
CONCLUSION: This study concludes that artificial intelligence wearable devices perform well in rehabilitating track and field athletes, providing a more scientific and comprehensive means of rehabilitation monitoring. Through Real Time tracking, the rehabilitation team could better understand the rehabilitation progress of the athletes, adjust the rehabilitation program in a targeted manner, and improve the rehabilitation effect. However, future research still needs to optimize the performance of the devices further, expand the sample size, and thoroughly study the monitoring needs at different stages of rehabilitation to better meet the individualized requirements of track and field athletes' rehabilitation process.

Keywords: artificial intelligence; sports medicine; wearable devices; track and field athletes

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*Corresponding author. Email: wubin7116@163.com

1. Introduction

Athletics includes a variety of competitions, such as running, high jumping, and throwing. For high school students and young adults, it is recommended to play specialized sports and participate in all physical activities[1]. Exercise is recognized as having health benefits, but there are indications that young athletes may experience adverse effects. Most research on the harmful effects of physical activity on the health of children and young people (e.g., sports injuries) has been conducted in the context of team sports, and few studies have been conducted in the context of individual sports.

Studies of young people playing sports have shown that the prevalence of sports injuries ranges from 35% to 65%, with a large proportion (65% to 95%) related to the lower extremities. Young people's most common sports injuries are neck strains, stress fractures, and ankle sprains. Factors influencing the risk of physical activity injuries in young people include physical activity, exercise load, and growth and development[2]. To avoid injurious behaviors, the author focuses on proper training programs during adolescence, but coaches don't know how best to move to prevent injury. Participants discussed the athletes' training areas, the shoes used, and their impact on injury development. Despite these observations, the possible mechanisms of sports injuries in children and adolescents have not been studied. The causes may be related to the methods of sports organizations in different countries, such as sports universities, schools, or educational institutions. In most parts of Scandinavia, the sport is mainly practiced in a club environment, which usually means small training groups consisting of several coaches who work together in teams of athletes. Training under these conditions challenges the needs of many athletes (parents/guardians) who also want to participate in longitudinal studies to determine causal relationships[3]. Epidemiologic studies are a prerequisite for understanding sport's different conditions and special needs. The main objectives of this annual prospective study were to characterize the frequency and types of sports injuries in athletes aged 15-25 years and to investigate possible risk factors for injury.

2. Relevant theories

2.1 Manufacturing technology for flexible wearable devices

Developing flexible, portable sensors requires innovations in materials science and manufacturing processes. Having described the main medical components of mobile medical monitoring devices, the author presents a production strategy to integrate each element into a functional system. Developing sensors, microprocessors, and compounds are usually based on micro-production methods such as chemical vapor deposition, atomization, reactive ion deposition, wet evaporation, thermal or electronic evaporation, and lithography. However, flexible micro-production methods often face challenges[4]. The protocol must first be executed on a complex silicon chip and transferred to a loose/scalable platform suited for human skin[5]. Chip rotation or assembly/removal methods can transfer laminate circuits. Low-temperature soldering or self-adhesive electrodes using abrasion-resistant AI devices can ensure deposition and good adhesion between different surfaces[6].

To avoid damaging the equipment, the internal connections of the system should be able to accommodate loads through the floor. This can be achieved by removing them from the earth or creating kirigami structures (e.g., serpentine). The material used to handle the solution is critical in scalability and reducing the cost of manufacturing the sensors. Therefore, different approaches are needed to develop flexible sensors. Artificial intelligence technology is beautiful because it reduces the cost of manufacturing equipment and is comparable to microfabrication techniques. It is also recommended to produce large sensors, as it is not limited to tiles production [7]. As a result, the transfer process is omitted, as the sensor can pass directly over a flexible plastic or flexible bottom. Another advantage of portable AI technology is its complementary nature, as the required sensor models can be stacked on top of the AI support and reduce the number of steps in the production process, resulting in fast production lines. In manufacturing flexible, portable electronic devices, the most commonly used technologies in the literature are mobile AI devices with screen printing capabilities and portable AI devices with rehabilitation capabilities[8].

Further research is needed before technologies such as concave surfaces and flexible AI vectors can be applied to commercial production. In recent years, research has shown that nanoscale lithography is an efficient, high-resolution mass-production method well suited for future portable medical devices[9]. Since the flexible sensor should be directly immersed into the elastic surface of the human body, special attention should be paid to the material design to ensure consistent, stable, reliable, and excellent performance[10]. In addition, the connecting tube structure can be optimized for the device's geometry to improve its tensile strength, as shown in the above examples[11]. Multi-pixel printing with specific patterns is a standard geometry in pressure sensor design, as distributed pixels allow for determining power distribution and have higher accuracy than mask structures used in flat layers.

2.2 Portable devices with artificial Intelligence and visualization technologies

AI devices are an advanced technology used for over 30 years to manufacture electronic devices with repeatability, reliability, and affordable mass production. A typical AI display system consists of a matrix, display, squeegee, and press. With the available AI technology, wing print counters are moving toward wing printing[12]. Specify the formulas for closed and open holes in the graphic grid, including the minimum size and thickness of the embedded holes. It is best to use a high-viscosity material (0.5-5 Pa3S) because low-viscosity materials pass quickly through the screen, reducing the resolution of the desired pattern. If the viscosity of the material is too high, the screen may clog, preventing the pattern from spreading ultimately [13]. Therefore, material properties and mesh density are important parameters that affect print thickness and resolution. The required circuit thickness for wear and tear of the AI network should be 5-250 mm, and the width should be 50-100 mm. Display AI devices have two parts: a flat AI carrier and a rotating AI carrier. Portable AI technology with a rotating display can provide high performance but is usually more expensive than flat transportable AI. The main disadvantage of AI screen weights is the loss of large amounts of irreversible material, which leads to additional wasted time because the network and model must be carefully cleaned after each use[14]. A piezoelectric device with AI has been developed to monitor physiological signals. Pet (polyethylene terephthalate) and paper are used as soft backgrounds. Piezo-voltage analysis has shown that wearable AI devices can use touch and force sensors[15]. Several researchers have demonstrated piezoelectric polymer network sensors connecting skin to AI devices—developing and exploiting different skin patches to detect gloves and prostheses[16]. The study measured the average piezoelectric constants of all asymptotic displacement (1-3N) sensors and provided detailed graphs.

In recent years, 3D printing technology (AM-RRB-3DR 3D printing technology) in various materials has transformed the manufacture of fully complex electronic components. Most 3D printing technologies use materials to print complex shapes. These nozzle technologies require low-viscosity materials (10-20 MPa3) for easy and repeatable material calibration compared to other AI wearable device technologies[17]. In this review, this paper examines and analyzes the impact of 3D printing on athlete rehabilitation. It is the most commonly used 3D printing technology for developing flexible ferroelectric medical devices[18]. The recovery effect of Print Athlete is a cost-effective, fully digital, and easy-to-use way to create scalable portable touch devices. Benefits of the process include low production temperatures, compatibility with various flexible substrates (flat or irregular surfaces such as paper, cotton, synthetic textiles, and polymers), reduced waste, deposit management, and additional design[19]. The color effect of the coffee creates a transparent ring around it, which affects the consistency of the pattern of the AI device. Athlete Recovery has two print modes: custom print mode and continuous print mode. The most common reporting model uses piezo nozzle drippers, which are more controllable and consistent than the CIJ printing system. The Athlete Regeneration Printer makes printing high-resolution conductive patterns on flexible materials easy. The performance of a portable printing device depends on the printed pattern's quality and the endpoint's mechanical flexibility, scalability, and longevity. Some researchers have used athletic recovery power printers to print polymer iron layers (VDF-TrFE) and polymer silver electrodes. The active layer of the sensors published under the influence of athlete recovery had piezoelectric properties (output voltage 250mV) with a dielectric constant (E0=12100Hz) corresponding to the thin layer covered behind[20]. A 7.8 mC/cm2 residual polarization and a piezoelectric coefficient of 10.4 pM/V were measured.d31 Some researchers have developed a sensor variant that uses a pressure technique to recover athletes from sprains.

3. Artificial Intelligence Wearable Devices for Monitoring in Athlete Rehabilitation

3.1 Introduction to the Methodology

This 52-week prospective study included boys and girls aged 12 to 15 and young athletes with parental/guardian consent. The ethics committee approved the study in October 2016 and registered with the clinic (NCT08267). Athletes could participate in the study provided that the sample population was a member club of a sports federation and participated in sports training at least once a week. To contact parents/guardians and obtain contact information, the primary activity should be youth sport rather than adult sport. Seventeen clubs in the study met these requirements and were contacted by telephone by the young researchers to ask if they would be interested in an annual prospective study. Written information was also provided to these clubs and those that could not be reached by phone. Ten clubs expressed interest in participating, and parents/guardians were provided with email addresses and invited to participate in the annual youth risk monitoring survey. Since all the young athletes were minors, obtaining consent from them and their parents/guardians was necessary. Overall, this 26-week study utilized a 52-week online survey system that collected data on athletic training and competition every two weeks. After four days, those who did not respond to the first email were notified. Parents/guardians sent all survey emails. Athletes were allowed to report training and injuries alone with the help of their parents/guardians.

$$FOM_{on-resonance} = \frac{k_{31}Q_m}{S_{11}^e} + \beta_0 \tag{1}$$

FOM in Equation (1) is the practical accuracy of the AI wearable, and β is the random error term.

$$Dig\_fom = \frac{d_{31}g_{31}}{\tan\delta} + \lambda_1 \tag{2}$$

Dig-for in Equation (2), i.e., the data-driven smart wearable, is considered digitized, and therefore, λ is the error term.

$$\theta_{ij} = ar\cos(\frac{Si \times Sj}{\|si\|\|sj\|}) \tag{3}$$

$$\left|\theta_{ij,cat} - \theta_{ij,sensor}\right| \leq \varepsilon_{\pi} \tag{4}$$

$$N_{\max} = floor\left(\frac{PR - D_{\min}}{eer_D}\right) + 1 \tag{5}$$

Equation (3) for the measurement of bone density directly with the inverse function arccos can be carried out; Equation (4) for the minimum Taylor term is less restrictive than the minimum error; Equation (5) for the determination of the maximum value of the natural number term N to be non-zero interpretation, so "$+1$".

During the first two weeks of the study, a baseline study was conducted in which participants were asked about their socioeconomic characteristics and specific information about the athlete's activities, such as frequency of workouts, frequency of workouts in the previous year, and possible muscle injuries. Training sessions and shoes were also collected as they increased the risk of injury. These variables should be included in the study report. That's why the two-week training report includes topics about training and game times, shoes worn, and games and other training venues during the previous two weeks. If a new injury occurs, a separate interview collects data such as the injury's date, the injury's context (sports, recreation, etc.), the onset of the injury (gradual/sudden), symptoms, area of injury, and nature. The health problem examined in the study was muscle injury, so recorded injuries were defined as possible new physical symptoms, including pain leading to reduced exercise load, difficulty in exercising or playing usually, or impaired athletic performance. Two physiotherapists categorized injuries as impairments (defined as conditions caused by identifiable external energy transfer) and non-impairments (defined as conditions caused by unknown causes) and classified injuries as being caused by progressive and sudden onset. Body parts were then categorized according to the International Classification of Diseases, Tenth Review, and Clinical Review [CID-10-SE]. The severity of the injury was determined in the weeks before exercise. Duration was calculated based on bi-weekly reports, biweekly reports, and week 0-52 reports. Severe trauma was defined as a lack of standard training for four to six months. Prolonged trauma indicates a lack of traditional training for more than six months. The level of iteration of the AI wearable is shown in Figure 1.

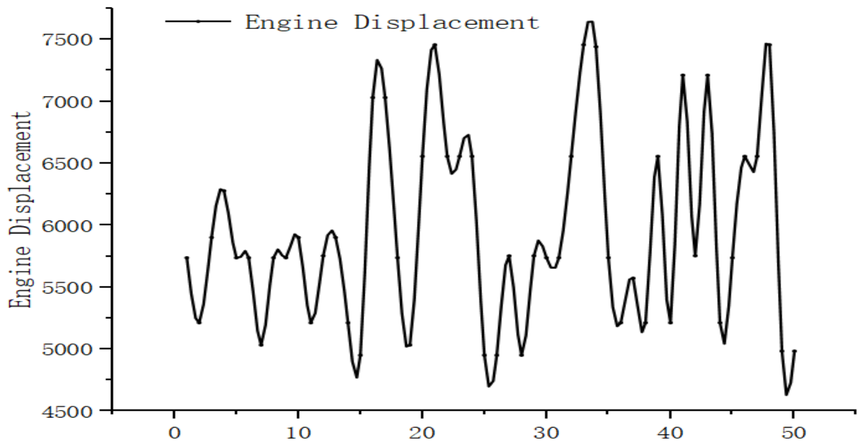

Figure 1. Iteration level of artificial intelligence wearable devices

3.2 Data processing and sample analysis

The time to first injury analysis was based on data from athletes over 52 weeks. Athletes (n=3) who were injured at the beginning of the test were evaluated until regular training. All data were assessed using descriptive statistics, including frequencies and percentages of categorical variables, quantities, means, standard deviations, averages, and continuous minima. Survival analysis was used to estimate the time to the first injury, calculated from the first day observed in regular exercise until the day of the reported injury. During the investigation, no athlete injured on the last day of a two-week training report was found to be examined. The most critical parameter in the results was the time of the first injury, measured weeks before the first injury. The time to first injury was analyzed using the Kaplan-Meyer method based on possible risk factors, and the mean time to injury was calculated using the Kaplan-Meyer curve. Appropriate diary tests should be used to investigate differences between groups/categories. In addition, Cox relative risk regression was used for multidimensional analysis from time to first injury, including possible risk factors. The following risk factors were discussed in the survival analysis: traumatic experience of at least three weeks in the previous year (yes/no), performance, frequency of exercise (including bi-weekly driving until an injury was reported within a week), and location of exercise (playing field, hard surface, soft surface, dirty surface). Training times and durations were reported every two weeks for different foot conditions (barefoot, shoes, or spikes) and then calculated as the average duration of each workout. The model also included a gender perspective and participation in sport (yes/no). The number of exercise sessions was calculated as the average duration of individual training in the two weeks following the first injury. The average number of hours reported per week was calculated if no injury was reported. They were categorized into 0-3, 4-6, 7-9, 10-12, and >12 hours per fortnight. Training frequency was categorized into exercise frequency, other, and total training frequency. The average two-week study period was based on the time since the first injury. If there was no injury, training time was calculated in the weekly training report. Due to the small number of athletes in this study, risk regression of coke ratios was limited to simultaneous multidimensional modeling of two factors. Missing data were not evaluated, and the researchers used only observational data for statistical analysis. All statistical investigations were two-way and statistically significant. Mean time to injury was calculated using the Kaplan-Meier estimate and shown as the 95% valid range (CIS). All calculations were performed using SPSS 26. Given the study's experimental nature and unadjusted diversity, P-values should be interpreted as nominal. The focus of rehabilitation monitoring in track and field athletes is shown in Figure 2.

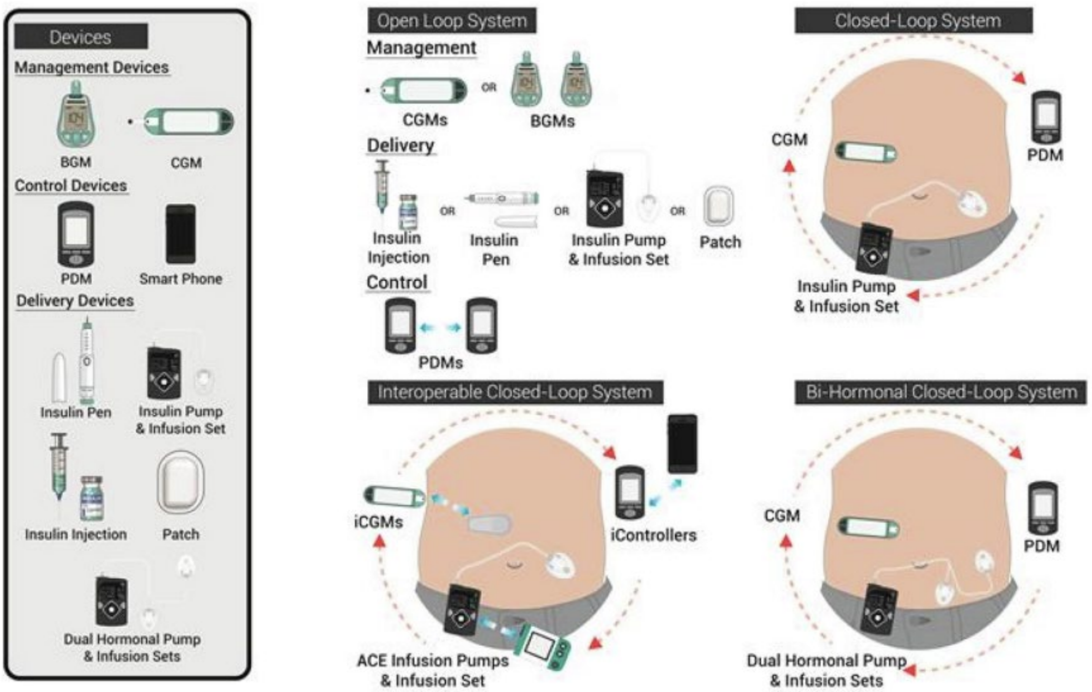

Figure 2 Rehabilitation monitoring priorities for track and field athletes[21]

4. Experimental results and discussion

4.1 Role of wearable medical devices for injury monitoring

One hundred eighteen young athletes and their parents/guardians participated and answered basic questionnaires. One hundred athletes (86%) reported at least every two weeks, 50 athletes (42%) wrote 32 weeks or more, and the overall response to exercise was 65%.39% of the athletes (33%) participated in other sports. Average training time for track and field and other sports. This year, 12 athletes stopped running and passed a rigorous survival test. If they trained every 10 hours, injuries would be 4.11 times more frequent. A total of 109 people were injured in sports. 54 (53%) young athletes reported a new injury, 29 (29%) reported two injuries, and 15 (15%) reported three or more injuries. The mean total duration of the first injury was 30 weeks (95% CI, 16-43%). Statistically, boys, on average, had a longer duration of first injury than girls.55% of young athletes competing in athletics for the first time recovered within two weeks, 70% within four weeks, and

85% within six weeks. The most common early injuries were non-traumatic (91%), progressive (51%), sudden (49%), and traumatic (9%). 85% of first-time injuries occurred in the lower extremities: thighs, groins, and thighs (28%), knees, calves (31%), and Achilles tendons, ankles, and legs/legs (26%). The most common early MKD-10 conversion injuries were quad and thigh injuries (S76.1) (13%) and nonspecific calf pain (M796G) (11%). Thigh tendon and muscle injuries (S.76.0 and S.76.1) accounted for 19% of first-time injuries. Logistic point tests indicated that athletes who trained more than 6 hours per week and performed peak training had a significantly higher risk of first injury. Multidimensional analyses of Cox risk-ratio regressions revealed significant interactions between learning time and peak uptime. Comparison of the results between the testing and rehabilitation periods and the areas of focus for rehabilitative exercise in track and field athletes are shown in Figures 3 and 4.

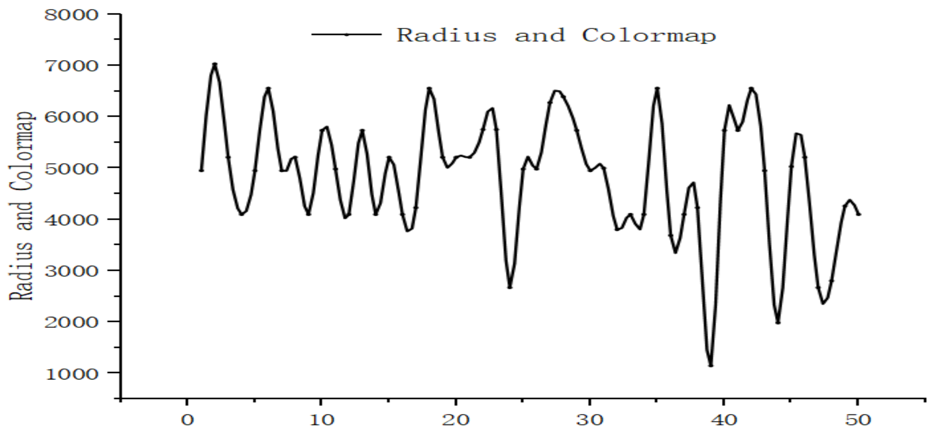

Figure 3. Comparison of results between detection and recovery periods

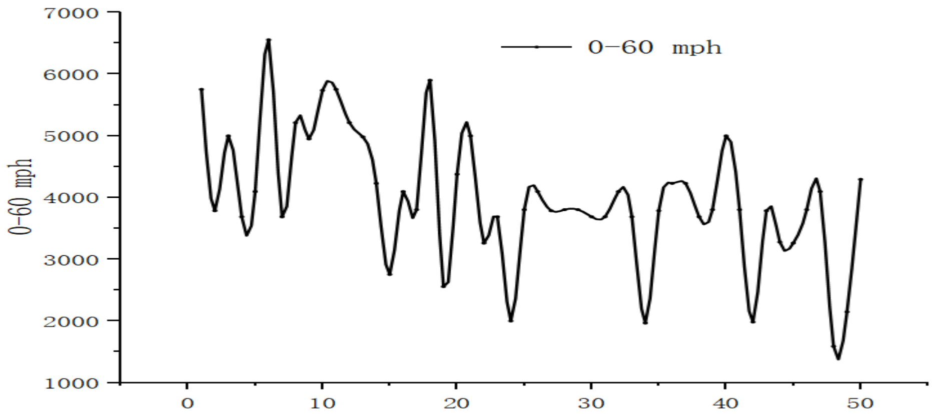

Figure 4. Focus areas for rehabilitation exercises for track and field athletes

4.2 Monitoring studies on the effects of rehabilitation

Nearly half of the young athletes were re-injured within a year, primarily due to assault. An exciting result of this study is the high number of femoral injuries that have not been reported to date. In addition to the researchers' knowledge, this is the first study in the field of track and field to examine the possible effects of training venues and shoes on injury risk in young athletes. The results suggest an interaction between ear use and injury risk associated with study time. The results of the bone density measurements are shown in Figure 5.

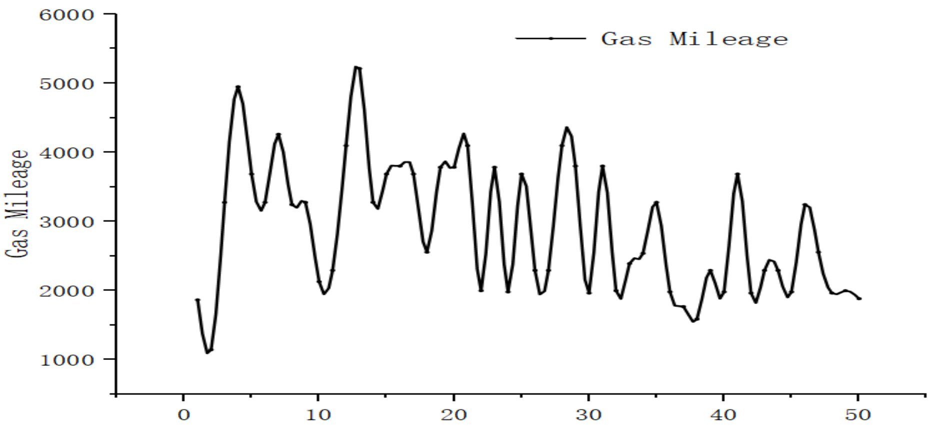

Figure 5. Bone density measurement results

The relatively high annual frequency index corresponds to the few published vertical studies. As with other sports, girls participating in sports appear to be more prone to injury than boys, and targeted action is needed. Following previous physical activity studies, young researchers found that most injuries (90%) were related to violence, with more than 80% occurring in the lower extremities. In some sports studies, the thigh was the most invasive area, and, as in other studies, researchers found that nearly 20% of injuries affected the thigh. Worryingly, the thigh quad complex accounts for almost 20% of new injuries, and the incidence of frontal thigh injuries in young athletes remains low. Reported femoral quadrilateral injuries in sprinting and soccer require a better understanding of the mechanisms leading to triple injuries in youth athletics because of the high risk of repetitive injuries. Many young athletes claim to struggle with this part of the body. Common diagnoses include mid-tibial tension syndrome and calf muscle growth pain. Notably, about half of the athletes began high-intensity training within two hours of their first injury. The findings may indicate that teachers and parents caused some of the trauma. However, three in ten athletes reported other injuries, suggesting they may have returned to play earlier. Injury history has been defined as a new indicator for adult and young athletes. However, the researchers did not find such an association in this study. The link between past trauma and post-traumatic trauma is thought to be complex and requires assessment and implementation of secondary prevention programs, as they set the stage for a safe return to education. A comparison of recovery outcomes for males and females is shown in Figure 6.

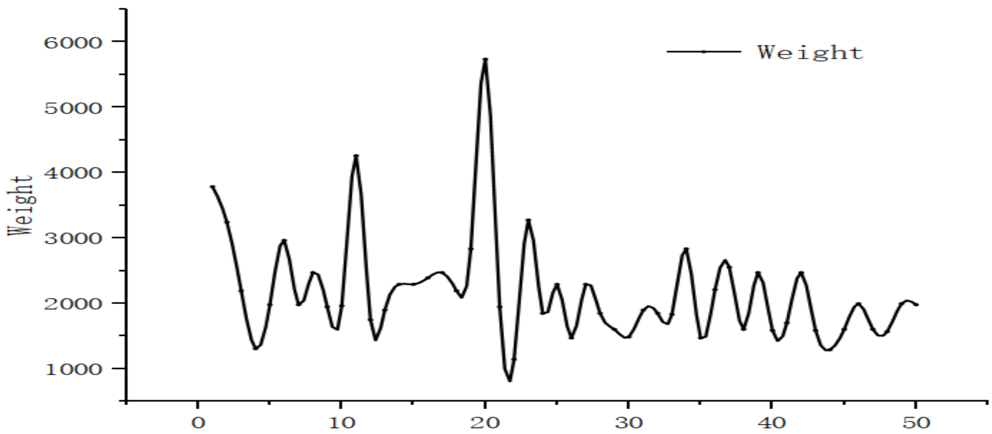

Figure 6. Comparison of rehabilitation outcomes among different populations

Early specialization, including the type of parallel training and the number of trained athletes, is associated with sports injuries in young people. Studies have shown this is linked to exercise frequency, with an eight times higher risk of recurrence after two weeks of exercise. Recommendations for young athletes in this age group: this means that the duration of training should not exceed the young person's age, but it is recommended to refer to the actual age of the athlete rather than the physical age. According to recent research, growth and maturation are associated with bone damage during exercise. In addition, during adolescence, this response changes with maturity, significantly stressing bone growth. The study found no correlation between injuries and training area, but researchers found that holding a ball every two weeks increased the risk of injury by about six times. The mechanism of injury caused by high-level track and field training is unknown but may be related to the type of top-level track and field training. This finding needs more attention because jumping and high-intensity running (sprinting and endurance) are essential for growing athletes. For young athletes and runners, high-intensity training and training loads are always associated with trauma. The report emphasizes that most factors related to athlete injuries are training errors. The report also stresses that the education of child and adolescent athletes requires an in-depth understanding of sport-specific training, the physical development and biological processes of young athletes, and their possible impact on injury. Recent research supports measures to prevent sports injuries in children, including a socio-ecological approach to developing sports among young people. The findings point in the same direction. Comparison of athletic ability and distribution of sports medicine problems in different cycles are shown in Figures 7 and 8.

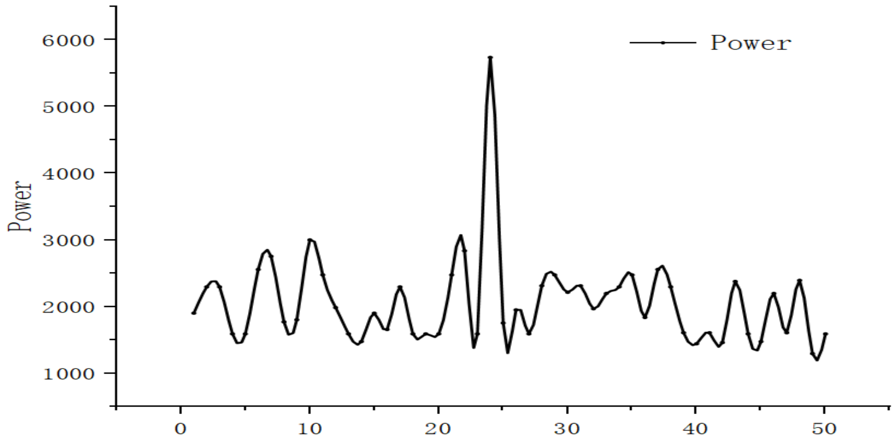

Figure 7. Comparison of different cycle movement capabilities

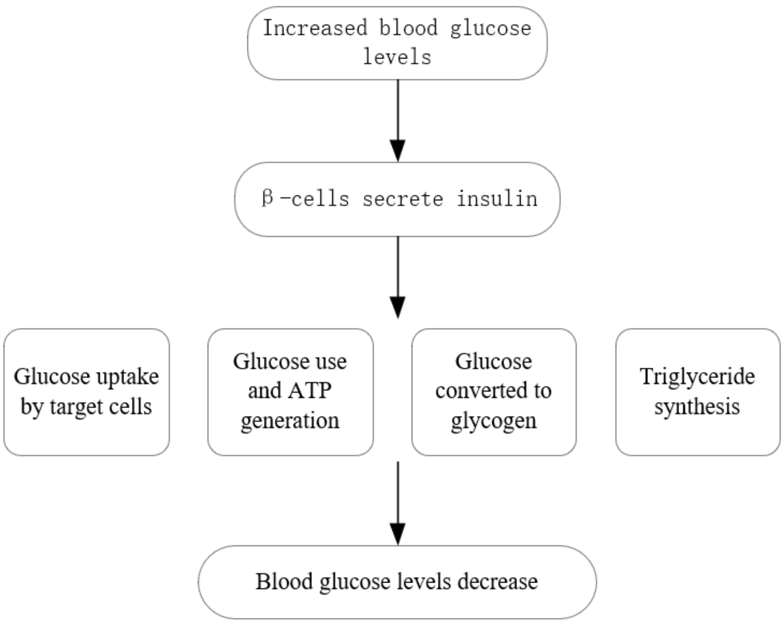

Figure 8. Distribution of sports medicine problems

The limitations of this study are that the study population was relatively small, and the exercise conditions could be particular, e.g., on the training ground. Therefore, the results cannot be immediately generalized to other sports groups. Another limitation is the accuracy of impairment assessments and self-assessment ratings, which depend on the participants. In this study, young athletes and parents/guardians reported all training and injury data, so it is essential to consider possible call distortion and the reliability of injury reports. The diagnosis was developed independently by two experienced physical activity therapists based on trauma questionnaire data from parents and their children, which may indicate an inaccurate diagnosis. However, the researchers concluded that older and younger athletes could effectively characterize new and body part injuries in younger athletes. Since this was a two-week prospective study, withdrawal errors were also considered minor. However, the reliability and validity of the survey were hampered by the lack of primary data and infractions, as well as insufficient training report data. There was no need to distort the estimates because the data were collected every two weeks, and the accuracy of the main variables was low. The risk factor analysis included athletes with first-time upper extremity injuries, but only three may have had minor deformities. The researchers included the athletes in the analysis because they felt that using the same population for all risk factors would be best. Because of these limitations, the strength of this study was a 52-week prospective program that investigated risk factors for injury.

5. Conclusion

Artificial intelligence wearable devices have shown significant potential and advantages in the study of Real Time monitoring of track and field athletes' rehabilitation effects. The following conclusions were drawn through the in-depth exploration of this study: firstly, AI wearable devices provide track and field athletes with more comprehensive and Real Time rehabilitation monitoring. Sensor technology enables Real Time access to crucial data such as athletes' physiological parameters, athletic postures, joint mobility, etc., providing rehabilitation teams with a more comprehensive tool for assessing rehabilitation status. This means that rehabilitation doctors and coaches can more accurately grasp the progress of the athlete's rehabilitation and adjust the rehabilitation program promptly. Secondly, Real Time monitoring strongly supports the personalization and targeting of rehabilitation training. Through in-depth analysis of the athlete's data, artificial intelligence wearable devices can build individualized rehabilitation models and identify the athlete's specific rehabilitation needs. This enables rehabilitation training to be more attuned to individual differences and provide more personalized and effective treatment plans. In practical application, it is observed that athletes show higher enthusiasm and initiative for rehabilitation monitoring when using AI wearable devices. Paying more attention to their rehabilitation status, they engage more purposefully in rehabilitation training through the Real Time feedback provided by the devices. This increased engagement is expected to further contribute to the improvement of athletes' rehabilitation outcomes. Despite the positive results of this study, some challenges and future research directions need to be noted. Issues such as the device's accuracy, comfort, and data privacy still need to be continuously improved. In addition, future research could further explore the applicability of different types of rehabilitation training to AI wearable devices and delve into the effects under long-term use. In conclusion, the application of AI wearable devices in the rehabilitation monitoring of track and field athletes demonstrates excellent potential and brings new opportunities to rehabilitation medicine. Through continuous technological innovation and research deepening, it is believed that more remarkable results will be achieved in this field, providing more scientific and practical rehabilitation services for athletes and further promoting the development of rehabilitation medicine.

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