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KEYWORDS	ABSTRACT
Wearable sensor, external workload, inertial workload, badminton,	Introduction: Badminton a fast paced and physically demanding sport the application of wearable sensors plays a crucial role in monitoring players' workload, injury risk, and recovery patterns. These technologies offer real-time insights into an athlete's physical exertion, allowing for personalized and data-driven coaching decisions. Objective: This review paper is to analyze and summarize the role of wearable and wireless sensor technologies in monitoring the workload of badminton players. Methodology: the methodology consists of a systematic review of literature search from internet using google scholar, PubMed and research gate. The review focusing on studies that employed wearable and wireless sensors to monitor workload, biomechanics, heart rate, and player movement. Results: Findings indicate that wearable sensors are highly effective in capturing key performance metrics such as jump count, footwork frequency, heart rate variability, and energy expenditure. These data points allow coaches and sports scientists to monitor player fatigue and adjust training loads accordingly. However, limitations such as sensor accuracy, user comfort, data privacy, and the cost of high-end equipment still pose challenges. Conclusion: Wearable and wireless sensor technologies play a key role in monitoring the workload of badminton players by providing important data on physiological and performance aspects. This helps coaches optimize training, reduce injury risk, and improve overall performance.
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Introduction

Badminton is an Olympic sport and ranks among the most popular racket sports globally. Whether for recreational or professional players, analyzing movements can significantly enhance the training process. There is a continuous search for technologies that optimize training to boost the individual performance of badminton players. This involves tracking and assessing player movements during both practice sessions and actual matches (Toohey et al., 2019). Tactics, technical skills, and precise movement execution are essential in badminton. Both players and coaches are interested in cost-effective, compact sensor technologies that can accurately capture the necessary data to provide valuable insights. In recent years, there has been significant research focused on recognizing and monitoring human activities, aiming to support performance analysis and training in sports like badminton (Laffaye, 2015). The increase in popularity of smart wearable devices, such as smartwatches and smartphones, has facilitated the necessary data collection process. These devices have many built-in sensors, such as a gyroscope, accelerometer and which are sufficiently accurate to be useful for the recognition of human activities (Arokanam et al., 2019). Activity recognition is very captivating, because it finds applications in a wide range of domains. Some of the interesting applications are tracking the physical activity of athletes predicting the movement of robots and vehicles using sensors (Gori et al., 2016).

In modern time developments of wearable sensor technology have made it possible to precisely identify human actions with great detail. Combined with advanced AI methods, this progress has enhanced the analysis of complex activities across multiple areas, including fall detection, sports training, healthcare support for individuals with disabilities, and rehabilitation (Zhang et al., 2022). While other fields focus on reducing the number and size of sensors used in research, the sports industry is adopting multimodal sensors to gain a comprehensive understanding of player movements and physical states. These sensors facilitate various analyses, from simple posture classification to performance analysis, and include inertial measurement units (IMUs) eye trackers pressure sensors skeleton tracking sensors electromyography (EMG) sensors and capacitive sensors (Lian et al., 2021). Multimodal sensors provide quantitative and objective performance data on players' performance, a feature that can be exploited to maximize the training effect for each individual (Oagaz et al., 2021). By providing in-depth analyses into joint movement patterns muscle activation and gaze movements sensor based tools offer a level of feedback that traditional coaching methods struggle to achieve (Ishibe et al., 2020). The responsibility of coaches to closely monitor every movement of their athletes can now be partially automated with the help of advanced technologies and AI-driven applications. This transition enables coaches to dedicate more time to delivering individualized feedback, tracking player development, pinpointing areas that need improvement, addressing specific weaknesses, and working on injury prevention strategies. By leveraging real-time data and automated analysis, coaches can focus on the nuanced aspects of athlete development that require (Terblanche et al., 2022).

Precise monitoring of training load is essential for elite athletes and coaches to design intense training programs while minimizing the risk of injury. Traditionally, coaches relied primarily on their subjective judgment and qualitative assessments to evaluate training loads (Liu et al., 2024).

In recent years, the use of wearable sensors for monitoring training has gained significant attention. Early studies in this field have shown promising results, identifying various variables that could be valuable and useful. Researchers in physiology and sports medicine often use the terms training load or workload to describe the total amount or volume of training and competition stress an athlete undergoes within a specific period (Vaha Ypya et al., 2015). The concept of training load often divided into two categories, internal training load and external training load. There are various measurement tools to monitor external and internal training load (Soligard et al., 2016). The internal training load represents the physiological response during training while the external training load describes the kinematics or kinetic data measured during training (Foster et al., 2017). Furthermore, sudden spikes in load have been linked to injury occurrences across a range of sports (Gabbett, 2016). Managing training loads in young athletes is particularly crucial due to increasing evidence showing a rise in overuse injuries within this group. Research has linked improper training loads to a higher risk of injury and illness among youth athletes. This highlights the importance of carefully planning and regulating training intensity and volume to promote healthy development and support a long, successful sporting career (Murray, 2017).

The gap highlighted in earlier studies, monitoring athlete workload has become a common practice among sports professionals, thanks to advancements in wearable sensor technology that allow for continuous measurement of various workload metrics. However, challenges remain due to inconsistent injury definitions, diverse methodologies, a lack of scientifically validated thresholds for functional workload ratios, and limitations in the mathematical approaches used to calculate these ratios. These factors complicate the task of establishing clear and meaningful links between workload and injury risk (Toohey et al., 2019). Wearable technology for tracking athlete workload is still relatively new, and there is currently no agreement on which sensor types should be used, which metrics are most relevant, how these metrics relate to injury, or how specific any observed workload-injury relationships are to particular sports or athlete groups. As a result, this scoping review included all studies that utilized wearable devices to monitor workload in team sport athletes, with special attention to research examining the connection between workload and injury (Ryan et al., 2020). Wearable technology is developing sports by providing real time data for players to improve training, enabling coaches to tailor strategies, and providing insights for the sports industry. This article explores the potential of wearable technology in sports, highlighting its potential to enhance players prowess, enhance safety, and provide more engaging sports experiences. This article aims to provide a comprehensive review of workload assessment in badminton using wearable and wireless sensors, with the broader goal of guiding future research in this evolving field. It explores the role of wearable technology wearable technology in sports, focusing on its components, practical applications, and the academic research conducted specifically within the context of badminton. The review highlights how wearable technology can effectively monitor physical performance, optimize training, and reduce injury risk by providing real-time data on player workload.

Players Load

Tracking the load an athlete undergoes during training or competition is crucial for assessing their adaptation to the training program, identifying recovery needs, and minimizing injury risk. In badminton, Player load has been compared to internal load indicators such as heart rate. Player load represents the total of a player's multidirectional accelerations and decelerations throughout a session, providing a comprehensive measure of physical exertion (Abdullahi et al., 2019). The need to manage loading in youth players is especially important as there is a growing body of evidence that has demonstrated an increase in overuse injuries amongst youth athletes and has linked inappropriate loads to injury and illness within this population (Murray, 2017). This evidence indicates that when dealing with youth athletes, planning appropriate loads and management of loading patterns is important to support a long sporting career. The metrics used to quantify external load are specific to the nature of training and include locomotive distance traveled, number of accelerations and mechanical number of jumps, frequency of impacts metrics, which can be recorded using wearable devices such as inertial measurement units (IMUs) and global positioning systems (GPSs). Internal load represents the psychophysiological response to external load and can be reported using subjective measures (session rating of perceived exertion),⁴¹ and portable heart rate monitors have allowed for the recording of objective internal load metrics heart rate zones and impulse (Bourdon et al., 2017).

Managing biomechanical load is especially important in youth athletes, as they are still developing essential movement skills and muscular strength. For instance, research on young soccer players showed that instances of knee valgus decreased as the athletes grew older and gained physical maturity (Read et al., 2018). In badminton, 64% of injuries reported among youth players were soft-tissue sprains and strains, with knee injuries being the most prevalent, representing 42% of all lower limb injuries. Understanding how load accumulates is crucial because the body adapts to different types of loading over varying timeframes. Such as physiological recovery may take just a few hours for a well-conditioned athlete, whereas recovery from biomechanical stress can require several days. (Vanrenterhgem et al., 2017).

Wearable sensors devise for workload management

Wearable sensors are currently being used to minimize injury in professional football via careful monitoring of training load and other biometrics during the rehabilitation period. The variability of GPS data and accelerations of the torso have been in question when it comes to monitoring the loads of the lower limbs. This is because distance traveled and velocity do not represent the mechanical load experienced by the musculoskeletal tissue (Edwards et al., 2019). This is specifically relevant in sports such as basketball, which are constrained to a small space, where players experience high loads of physical stress by performing explosive jumping and landing activities, which are not accurately captured by distance, speed, or torso athlete movement analysis systems (Impellizzeri et al., 2019).

Many studies have sited accelerometers on athletes' upper backs to measure Player load (PL). However, for racket sports or non-contact sports, placing accelerometers on the four limbs and

lower back may be more practical and offer more detailed information about specific activities. It is important to note that racket sports involve complex movements that engage both the upper and lower extremities, often with asymmetrical actions between the racket and non-racket sides. This can lead to distinct characteristics in the external training load captured by accelerometers depending on their placement during the execution of racket skills (Polglaze et al., 2015).

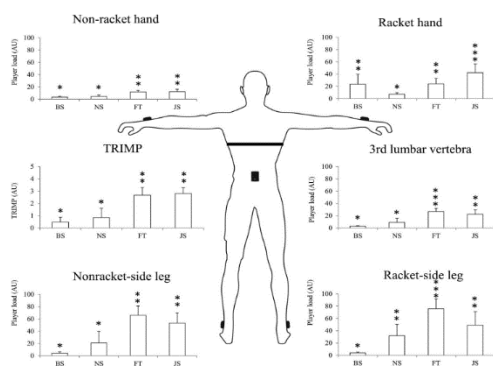


Figure 1: Location of accelerometer in during playing (Liu et al., 2024)

Player load measured from different location reflect external load of the local limb. This is meaningful to quantify training load of local limb, such as racket hand load and lower extremities. Moreover, the sensing device placed on racket-hand could be applied to monitoring the hitting load for prevention of over-training injuries (Genevois et al., 2018; Whiteside et al., 2017).

Accelerometer

Accelerometers are a common sensor found in wearables. Their sensing capabilities range from different types of accelerations (linear and gravity). Their measuring capabilities allow monitored data to be programmed for different uses (Aroganam et al., 2019). When a user runs, it can output top speed as well as acceleration. Accelerometers also monitor sleep patterns, which can be linked to seizures. It is important that the programmed algorithms must not be affected, as this can corrupt the monitored data during processing phase. This will make the monitored raw data meaningless (Del et al., 2016).

Gyroscopes

Gyroscopes are another common sensor found in wearables. They differ from accelerometers in that they measure angular accelerations exclusively. Some applications will prefer to use the accelerometer to determine rotational acceleration, whereas some would want to combine both in order to filter errors. This is to increase the accuracy of the monitored data. There are different types, such as gas bearing, optical, and mechanical (Passaro et al., 2017). Optical is the one that works differently (non-angular momentum), where the two fiber optic coils are spun in alternating directions, thus they travel different distances, which is monitored (Sagnac effect). Gyroscopes essentially detect angular velocity on their disk. Vibration gyroscope sensors sense angular

velocity due to the Coriolis force. These are natural forces that occur due to Earth's rotation, which acts on a vibrating element. The motion produces a potential difference that gets converted into an electrical signal. This is used for measuring orientation and projection, making it beneficial for stats that involve angles or specific positioning. The method of tracking also means that the location of the sensor can be influential in data collection. If there is a need to integrate the sensors with equipment, another consideration to factor will be selecting compatible electronics and locations around those sensors (Mitschke et al., 2017).

Sensor derived parameters

Sensor-derived parameters play a critical role in analyzing movement and workload, especially in sports science applications such as monitoring the performance and physical demands of badminton players. Data from sensors like gyroscopes, accelerometers, and magnetometers can be used independently or in combination to extract meaningful metrics that reflect an athlete's biomechanics and physical exertion (Taborri et al., 2020).

Temporal parameters

Temporal parameters refer to time-based characteristics of movement. These include variables such as step time, contact time, flight time, swing duration, repetition count, and movement frequency. They are commonly used to quantify the rhythm or timing of movement patterns during specific tasks, like footwork sequences in badminton. Detection is often based on identifiable peaks, troughs, or changes in signal amplitude in accelerometer or gyroscope data. For instance, in high-speed sports movements, temporal data helps segment different phases of action such as preparation, execution, and recovery (Camomilla et al., 2018).

Purpose and scope of the study

Badminton is an intense sport that demands exceptional fitness, agility, and coordination. Players engage in diverse movements such as jumping, lunging, and quick directional changes, which place considerable stress on their musculoskeletal system. This review aims to explore and synthesize existing research on the use of technology to collect data on physical activity, physiological responses, movement patterns, and external load during both training and competition. It examines various types of sensors, their applications, accuracy, advantages, and limitations specifically within the context of badminton. Furthermore, the study highlights emerging trends, identifies research gaps, and highlights recent advancements in sensor-based workload evaluation. The paper aims to provide insights into how these technologies enhance performance optimization, injury prevention, and personalized training approaches. By summarizing and critically appraising previous work, this review serves as a valuable resource for guiding future research and practical implementation in sports science and athlete monitoring.

Method

The researcher search literature for articles was performed on the internet using PubMed, google scholar and research gate over the past twelve years. The study's development was based on an extensive literature review of past work relevant with the keywords such as workload mentoring through wearable sensor of badminton Players.

Inclusion criteria

Research that utilizes wearable wireless sensor technologies. Articles published in peer-reviewed journals, conference proceedings, or reputable academic sources. Studies focusing on training load, match performance, physical exertion, and injury prevention in badminton using sensor-based tools. Full papers published in English.

Exclusion criteria

Articles that focus only on technical or tactical analysis without addressing physical or physiological workload. Studies not available in full text. Paper not published in English. Studies published before 2014 were excluded.

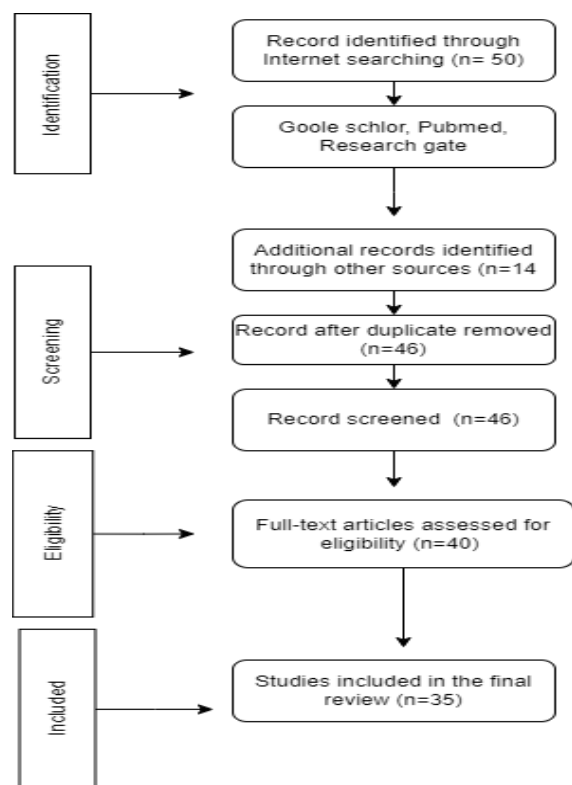


Figure 3: Study flowchart for systematic search of articles on workload monitoring of badminton players using wearable and wireless sensor

Figure 3 shows the selection process of studies included in the review on workload assessment of badminton players using wearable and wireless sensors. A total of 50 records were initially identified through internet searches using academic platforms such as Google Scholar, PubMed, and Research Gate. An additional 14 records were found through other sources, including reference lists and manual searches. After removing duplicates, 46 records remained and were screened based on their titles and abstracts to assess relevance. Of these, 40 full-text articles were retrieved and assessed for eligibility using predefined inclusion and exclusion criteria. Finally, 35 studies were found to meet the criteria and were included in the final review. The flowchart presents a clear and systematic approach to the study selection process, ensuring the inclusion of only relevant and high-quality literature.

Discussion

The aim of this systematic review was to investigate the methods used to monitor workload of badminton players using wearable sensor. From the studies included in this review, it was apparent that workload-monitoring techniques are not advanced in badminton, although simple monitoring methods have been shown to have the capacity to identify injury risks and injury thresholds in instances within these sports. Based on the review article wearable and wireless sensors have demonstrated significant potential in monitoring and managing the workload of badminton players, several limitations of current technologies must be acknowledged. One of the primary challenges lies in the battery life of wearable devices, which often restricts continuous monitoring over extended training or match durations many current systems face difficulties with real-time data processing limiting their usefulness for immediate decision-making during training sessions or competitive play (Khan, 2022). The accuracy and consistency of sensor data, especially in high-speed, multi-directional sports like badminton, where rapid changes in movement and intensity can lead to data fluctuations or sensor misreading. The lack of sport-specific calibration also reduces the precision of workload assessments, particularly when generic sensor models are used without tailoring to badminton's unique movement demands (Camomilla et al., 2018).

Furthermore, although this review focuses on badminton, comparisons with other racket sports such as tennis and squash reveal both similarities and differences in how wearable technology is applied. In tennis, wearable sensors are widely used to monitor stroke count, movement load, and fatigue levels while in squash, high-intensity rallies have pushed research into more advanced heart rate and motion tracking (Reid et al., 2016). Implementing these technologies in real-world training environments also presents several challenges. Coaches and athletes often face barriers in interpreting complex data outputs, which can reduce the practical value of these tools (Bourdon et al., 2017). Many teams lack dedicated sports scientists or analysts to translate raw data into actionable insights, making integration into daily routines difficult. Additionally, cost and accessibility remain concerns, especially for amateur or youth-level programs that may not have the resources to invest in advanced wearable systems.

Conclusions

In conclusion, this review paper underscores the pivotal importance of wearable and wireless sensor technologies in effectively monitoring the workload of badminton players. The systematic analysis reveals a range of straightforward yet impactful monitoring techniques that have been applied not only in badminton but also in various other sports. Although these technologies are still relatively underutilized in badminton compared to disciplines like soccer, basketball, or athletics, their potential to optimize performance, reduce injury risk, and support individualized training regimens is substantial. Key sensor-derived metrics such as acceleration, movement timing, joint angles, and limb-specific load distribution offer valuable insights into the sport's intense physical demands, aiding in both training and recovery management. However, include technical challenges such as including issues related to battery life, data accuracy during high intensity movements, real time feedback capabilities, and the need for sport specific calibration. Moreover, practical implementation is often challenged by the complexity of interpreting sensor data and the limited access to technical support in non-elite settings. As the field advances, future research should focus on improving the accuracy, usability, and affordability of sensor systems tailored specifically for badminton. Doing so will enable broader adoption and more effective integration into training and competition environments, ultimately supporting athletes' development and long-term health.

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