Wearable Applications in Rugby for Performance Quantification and Player Health Assessment: A Brief Review

Colbert Lehr[a], Othmane Omalek[b], Sam Osborne[c], Zachary Warren[a], David Saucier[d], Reuben F. Burch V[c,d], John Ball[a], Harish Chander[d,e]

[a]Electrical & Computer Engineering, Mississippi State University, Mississippi State, MS, USA

[b]Mechanical Engineering, Mississippi State University, Mississippi State, MS, USA

[c]Industrial & Systems Engineering, Mississippi State University, Mississippi State, MS, USA

[d]Human Factors & Athlete Engineering, Center for Advanced Vehicular Systems, Mississippi State University, Starkville, MS, USA

[e]Neuromechanics Laboratory, Department of Kinesiology, Mississippi State University, Mississippi State, MS, USA

Corresponding Author: Reuben Burch, E-mail: burch@ise.msstate.edu

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ABSTRACT

Background: Wearable technology use in sports has amassed increased attention in recent years. Technological advancements have provided less labor-intensive methods for practitioners and athletes to track kinematic movements, workload metrics, and biometric markers to assess performance and safety. As such, wearables research has spread to a variety of sports; however, the specific wearable technologies used in the rugby codes—rugby league and rugby union—have not been reviewed. **Objective:** Herein, we present a review that aims to understand the use of wearable technology for performance demand quantification and player health assessment in rugby league and rugby union. **Method:** We classify extant scientific wearable literature into four research categories: Prehabilitation (preventative rehabilitation), Performance, Rehabilitation, and Data Analysis. **Results:** Eighteen articles were found using predefined inclusion and exclusion criteria and were grouped into these four research categories. Through this review process, Global Positioning System or GPS-based wearables were found to be utilized more when compared to all other wearable devices associated with peer-reviewed studies for the sport of rugby. In general, wearables were found to be used to support player and practitioner efforts to promote health and ensure peak performance prior to competition. Wearables were also used to determine injury severity and mitigation strategies—such as collision monitoring—and to develop positional activity profiles. **Conclusion:** Data collected through wearable technology may enhance rugby conditioning programs by enabling the tracking of numerous aspects of training performance and safety in competitive match play. Future research is warranted for standardization of player evaluation and injury predictive modeling.

Key words: Rugby, Wearable Electronic Devices, Exercise, Preoperative Exercises, Athletic Performance

INTRODUCTION

Athletic applications of wearable technology have become a tool of choice for tracking athlete health and quantifying match performance to ensure optimal decisions are made before, during, and after a match. This growth is proliferated by increased availability and affordability of sensors for data capture (Burch et al., 2019). Market valuations reflect this growth, as the sports technology market valued at USD $8.9 billion in 2018 is expected to reach USD $31.1 billion by 2024 (MarketWatch, 2021). Rugby is no exception to this explosive growth given the record viewership of the 2019 Rugby World Cup increasing by 26% from previous tournaments with 857 million viewers (Rugby World Cup, 2020).

However, there exists a notable gap regarding wearables and the sport of rugby. Most of the existing research is focused on specific implementations of a wearable or analysis of sensor data with limited research on player management using wearables in such sports (Alderson, 2016; Powell et al., 2020). Seeing this opportunity, we sought to fill this gap by presenting existing research in a comprehensive format. While gathering the literature, it was noted that each article could be classified into one of four categories: Prehabilitation (preventative rehabilitation), Performance, Rehabilitation, and Data Analysis. These four research categories were selected based on previous research by the team to understand what practitioners in the field of strength and conditioning and athletic training consider critical for their health and safety decision making (Luczak et al,

2020). These categories demonstrate how wearables can be used in the various aspects of the sport such as training for the sport, occurrences during the sport, and recovery once the game is completed. The Prehabilitation category consists of wearables designed to mitigate the risk of injury prior to a match to ensure peak performance. The Performance category discusses the use of wearables for quantifying various performance metrics during a rugby match. Wearables are also used in the Rehabilitation process to ensure player performance post-injury is on par with expectations before reintroduction into another match. Finally, the Data Analysis section describes methods used to extract usable data from the mass of sensor readings recorded before, during, and after a match.

METHODS

Study Design

For this narrative review, search terms were generated based on insights from the research teams' previous experience in wearable technology and interactions with coaching staff and human performance practitioners from collegiate and professional sport organizations. A list of key terms regarding the use of wearable technology for the assessment or management of elite rugby athletes in terms of their performance and health was compiled. A literature search was subsequently conducted for digitally available resources with EBSCO and Google Scholar. EBSCO is the university library research database that includes all other research databases so that when key terms are entered in the EBSCO search tool, all academic databases are searched and then represented in a single list within the library interface. Key terms included in the search are presented in Table 1.

Literature Search

The literature search was conducted from January 2021 through February 2021 via the EBSCO and Google Scholar databases as primary sources. Mendeley resource management software was used to house, organize, and allow all team members to access and review all articles. The resources found through the literature search mostly consisted of peer-reviewed articles published between the years 2002-2020. Search terms used comprised the topics of the sport of rugby league and rugby union, device, match/training performance, and player health (Table 1).

Data Extraction and Analysis

The PRISMA method was utilized for discovering relevant literature in the rugby wearable domain investigated for

Table 1. Key terms used in EBSCO and Google Scholar literature search

'rugby' OR 'rugby league' OR 'rugby union' AND 'global positioning system' OR 'inertial measurement unit' OR 'microtechnology' OR 'wearable' AND 'movement' OR 'impact' OR 'scrum' OR 'scrummaging' OR 'machine learning' OR 'collisions' OR 'analysis'

this paper. Identified literature was assessed with respect to relevance and standardized inclusion and exclusion criteria to maintain a consistent process. Search results were chosen upon fulfillment of the following requirements:
1. Full-text article available
2. Available in English
3. Found in a peer-reviewed source
4. Not an exact duplicate
5. Fit within the context of the inclusion criteria:
    a. Application of wearable technology
    b. Effectiveness on performance and/or health
    c. Evaluation of performance and/or health
    d. Limitations of wearable technology

Upon reviewing the literature, anecdotal and empirical assessments of wearable technology utilized for managing athlete performance and health were identified and assessed. Figure 1 describes the literature review process and notes how many articles were found and excluded during the process such that findings from this study can be replicated and future studies can expand upon this review as more assessments of wearable technology in elite rugby become available.

Study Selection

The literature search revealed 1084 articles, identified through EBSCO and Google Scholar as primary databases, to meet the aim of the project. Initially, 893 articles were excluded according to the defined exclusion criteria; that is, the articles were written in a non-English language, were published in a non-peer-reviewed journal, were duplicates, or did not relate to the paper aim as they were not rugby related and/or did not make a clear statement on the performance and health management of the wearer. The remaining 191 articles were subsequently assessed for relevance according to Eligibility Criteria 1-4, and a total of 18 articles were identified as suitable given the context of the criteria. The inclusion/exclusion process is described in Figure 1. An analysis of the content of the articles was conducted by reading the abstract of the article along with the key findings outlined in the discussion sections, whereupon it was noted extant literature could be classified into four research groups: Prehabilitation, Performance, Rehabilitation, and Data Analysis. Of the 18 identified articles, four contained information concerning the use of wearables to mitigate injury risk prior to a match (Prehabilitation). Seven described the use of wearables for quantifying various performance demands before, during, or after a rugby match (Performance). Four articles contained information concerning the integration of wearable technology in the Rehabilitation process. Three described or assessed methods used to extract and evaluate usable data from the mass of sensor readings (Data Analysis). In the subsequent sections of this review, research of particular importance or notability is reviewed in detail.

RESULTS

To summarize the key results from all the studies associated with wearable technology, rugby-based research, Tables 2 – 5
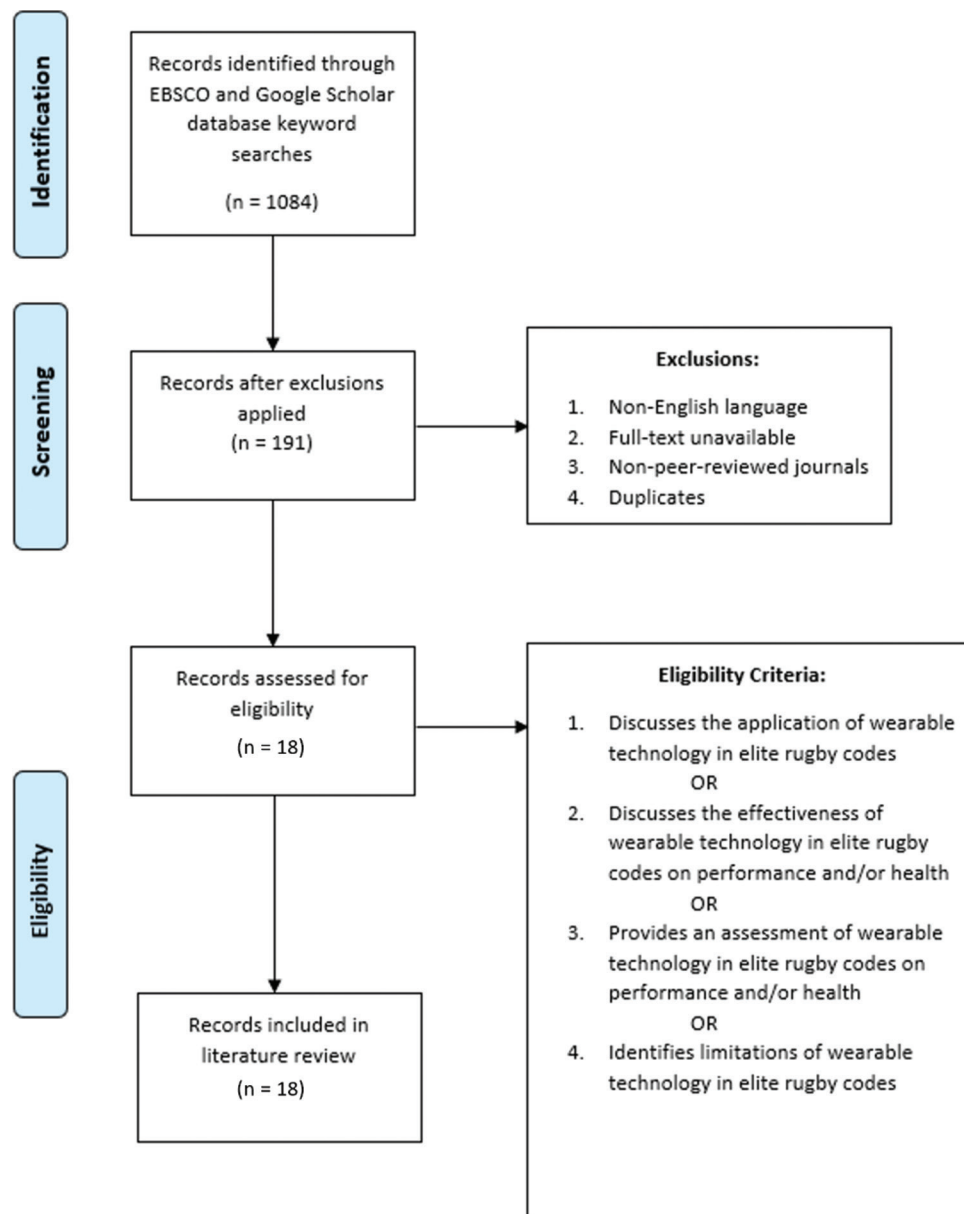
Figure 1. PRISMA diagram representing article selection flow

detail the lessons learned for practitioners looking to quickly assess the state of the air in this human performance sector.

DISCUSSION

Pre-rehabilitation

Rugby is a high contact sport where the injury risk to a player is constant (Bird et al., 1998; Fuller et al., 2008). Therefore, wearables have been developed and tested to mitigate injury risk and keep track of a player's health before a game to ensure peak performance. One type of wearable that has been employed, mentioned by Glassbrook et al. (2020), is the inertial measurement unit (IMU). By using IMUs, data can be collected on the mechanical load of the lower limbs to determine if the player is at risk of injury. This can be done by comparing the angle of the limb to a threshold where 15 degrees or greater is considered dangerous to the player. Coaches can use this method to accurately monitor their players to ensure safety.

Monitoring a player's lower limb functional status is needed, but in rugby, there are risks of injuries to the upper body as well. According to Alderson et al. (2016), shoulder injuries are the most common. Another wearable, known as the LiveSkin™, was developed to monitor the contact collisions that were occurring during a practice or game (Alderson et al., 2016). The main purpose of this study was to monitor between the impact between two players more than any non-contact collisions. The device monitors the player's fatigue along with the force development of the sensors. Through testing, the accuracy of the LiveSkin™ is high which allows it to detect a wide range of collisions on the field (Alderson et al., 2020). An aspect of the LiveSkin™ that is the most beneficial is the fact that it can be used to recognize if a player has fully recovered from an injury or not. LiveSkin™ is placed in the shoulder pads and captures measurement readings of how much force has been applied as well as the fatigue levels of the muscle groups. The data

Table 2. Summary of findings, recommendations, and limitations for wearable use in rugby pre-rehabilitation

Pre-rehabilitation				
Citation	Wearables	Findings	Recommendations	Limitations
(Alderson et al., 2016)	LiveSkin™	The LiveSkin™ has high accuracy with wide range collisions and is comfortable to wear.	Strength and conditioning coaches can use this device to mitigate injuries of players.	Due to lack of knowledge with specific technologies being used, it still must be reviewed and understood.
(Gabbett et al., 2012)	MinimaxX™	Players who perform collisions have more high-intense interactions while those without collisions ran greater distances.	The players can determine what exactly they should focus on in respect to their position.	More research is needed to determine if the training regimens need to be reevaluated.
(Glassbrook et al., 2020)	IMUs	By connecting an IMU to the boot of a player, the mechanical load on the lower limbs were detected with high accuracy.	By keeping track of the load on the lower limbs, injuries can be mitigated.	When players slowed or collided with another player, the IMUs read inaccurate data during that period.
(Jones et al., 2015)	GPS	Positional differences varied for each player uet were able to be recorded successfully.	This data can be used to developed drills to enhance player performance.	Temporal analysis was not as successful since the training regimen and the finals loadings were significantly different between all players.

collected is used to determine if a certain player is in proper condition to play at the next game.

Global positioning system (GPS) devices enable practitioners to record and synchronize time, velocity, and location data over multiple athletes and represent the most abundant tool of choice in the studies assessed here. Of the 18 articles reviewed for this study, nine focused on GPS as the main source of data collection. Indeed, research applying GPS devices surged beginning in 2013, with the technology described as "almost essential" to elite sporting teams in a review of GPS applications in rugby (Hausler et al., 2016). In terms of Prehabilitation, practitioners can utilize GPS devices as a tool for comparing the physical demands of rugby matches to typical training activities to better manage players for competitive bouts (Gabbett et al., 2012). Further, the quantification of positional and/or temporal movement demands, patterns, and characteristics by player position is described in several studies, all of which identified herein demonstrate plausibility to develop position-specific training drills rather than group positions together. The differences in various demand factors between position groupings as well as specific positions is well documented. Austin & Kelly (2013), Gabbett, et al. (2012) and Jones et al. (2015) each describe discrepancies in elite rugby positional demands using GPS match data. While studies that use GPS sensors and their data to evaluate positional differences have been used to inform drill development and help optimize training (Hausler et al., 2016), it is important to note the utility of these studies' results are confounded by either low GPS sampling rate (≤ 5 Hz), small game sample size, or small player sample size, eliciting more general recommendations. The two major GPS systems used in rugby are developed by Catapult® Sports (Catapult Sports, Melbourne, VIC, Australia; MinimaxX™ device) and GPSports (GPSports, Canberra, ACT, Australia; SPI-Pro II™ and SPI HPU™ devices; Hausler et al., 2016). Further studies utilizing GPS will be discussed in the Performance and Rehabilitation sections.

Performance

Rugby is an intermittent high-intensity sport characterized by maximal strength activities like sprinting, tackling, rapid acceleration/deceleration, and scrummaging, interspersed with less intense aerobic activities like walking or jogging (Chambers et al., 2019b; Cunniffe et al., 2009; Istvan Rydså, & van den Tillaar, 2020). Athletic performance in the sport is therefore multifactorial, composed of tactical, technical, and physical components (Henderson et al., 2019). Through the years, monitoring systems for optimizing athletic performance in rugby have been developed (Kelly et al., 2012). Initial studies utilized time motion analysis and game video recordings to quantify physical demands, but issues involving the reliability and practicality of these devices displaced this method when less time-consuming and labor-intensive wearable technology became readily available (Barris & Button 2008; Gabbett, 2013; Kelly et al., 2012; Roberts et al., 2008).

A few studies seek to quantify the demands of the rugby codes by replicating early research in other collision sports like American football, but this is difficult for a few reasons. Rugby players utilize minimal protective padding compared to American football players, so sensor placement varies. Contact events differ in their dimensions for each sport and significantly between rugby union and rugby league. Consequently, attempts to apply algorithms between sports, even from one form of rugby to another, have been unsuccessful (Chambers et al., 2019a).

A common use of wearable technology in rugby is investigating collisions, which are defined as alterations to a player's momentum resulting from contact with another player (Gabbett et al.,2010). During rugby matches, the tackle, the ruck, and the scrum are reportedly the most frequent contact events that occur, and team success is dependent on a group's ability to endure these events to win (Cerrito et al., 2019; Chambers et al., 2019b; Hendricks et al., 2018; Roberts et al., 2008). In addition to being one of the most import-

Table 3. Summary of findings, recommendations, and limitations for wearable use in rugby performance

Performance				
Citation	**Wearables**	**Findings**	**Recommendations**	**Limitations**
(Cerrito et al., 2019)	EMT	The kinematic patterns of the cervical spine were different between machine and live scrummaging which makes the generalization of research not as accurate.	Coaches should keep track of the players cervical spine during scrummaging, and this could also help the players with better posture.	The data gathered was on a set schedule due to training hours of the players. A randomized study would be beneficial to the data gathered.
(Chambers et al., 2019a)	Catapult OptimEye S5™	During the training set, the first two rows were most accurate, but during the testing, the last two rows were most accurate in detecting scrummages.	The algorithm is useful for quantifying scrummage events in a rugby elite game.	False negatives occurred in the algorithm when fewer players were present. To ensure accurate data, at least 5-8 players need to participate.
(Chambers et al., 2019b)	Catapult OptimEye S5™	The Catapult S5™ accurately counted collisions which was used in an algorithm to get accurate data on the number of collisions and contacts in Rugby.	The data gathered can be used to mitigate future injuries.	This study only used one team in an international league. Due to different training methods, this algorithm may not produce the same results when used with other teams.
(Cummins & Orr, 2015)	SPI-Pro X™	During a rugby game, players encounter significant numbers of collisions. Depending on the position of the player, some may encounter more collisions than others.	Coaches can use this information to better prepare their players for their specific positions.	The accelerometer that is being used to record data can be increase to the range of 8-12g. This could lead to classification of collision intensity to be inaccurate.
(Cunniffe et al., 2009)	GPS, Polar Electro™	The use of a GPS unit and a heart rate belt demonstrated accurate data on physiological demands during a rugby game.	Coaches can use this data to determine individual players stress during a game and the approach needed to better prepare the players.	This study focused on two individuals and their specific conditions. This cannot be used for a generalization of a team but rater individual human performance-related outcomes per player.
(Hulin et al., 2017)	Catapult OptimEye S5™	The use of the Catapult S5™ results in 97.6% accuracy when detecting collisions in a rugby match.	The information gathered gave coaches a measurement of workload that is being applied when players collide.	The device was inaccurate mainly when the collision impact was mildly low, so collisions were not detected at lower impacts.
(Reardon et al., 2017)	Catapult OptimEye S5™	The OptimEye S5™ working beside its software is not an accurate method when determining collisions in rugby.	Coaches can use this knowledge and data to be weary of what they use to track data on their players.	This study did not separate the different types of collisions such as tackles, rucks, etc., Therefore, further studies should be done to determine if it works better with certain type of collisions compared to others.

ant skills in rugby, tackling also accounts for the most rugby injuries (Gabbett et al.,2010; Gabbett, 2013). Along with the ruck and the scrum, the tackle is extremely important to assess quantitatively and technically. Several studies utilize wearables to accomplish this.

Cerrito et al. (2019) assessed cervical spine kinematics in rugby union players scrummaging against a scrum machine and against live-game opponents using an electromagnetic motion tracking (EMT) system with two sensors: one on a player's chest and another on the head. Cervical spine kinematics are considered head movement relative to the thorax. EMT data requires denoising, but by utilizing EMT, the researchers generated a local coordinate system for a player's head and thorax. They were also able to perform separate kinematic analyses on the upper and lower cervical spine with the data. A shortcoming of EMT is its sensitivity to electromagnetic fields, so large metallic objects needed to be documented and removed for the study. This limits the use of EMT in generalized studies.

Other means of investigating collisions in rugby matches with wearables include GPS and microelectromechanical systems. Chambers et al. (2019a) and Hulin et al. (2017) use Catapult S5 Optimeye™ devices in combination with custom designed algorithms to identify collision events in competitive matches. Their research added to previous work like Gabbett et al. (2010), who used Catapult MinimaxX™ de-

Table 4. Summary of findings, recommendations, and limitations for wearable use in rugby rehabilitation

		Rehabilitation		
Citation	**Wearables**	**Findings**	**Recommendations**	**Limitations**
(Coughlan et al., 2011)	SPI Pro™	By using a GPS wearable, the physical demands of players can be monitored and determined.	The sports medicine practitioners could use this data to help in future rehabilitations.	Only two participants were in the experiment which leads to minimal data points for analysis.
(Howe et al., 2020)	Catapult OptimEye S5™, GLO-NASS™	GPS and accelerometers have poor sensitivity for some movement types.	GPS and accelerometers should not be isolated when gathering data on athletic movement.	GPS generally only works properly outside; accelerometers work better indoors.
(Li et al., 2020)	Catapult OptimEye S5™, Catapult Sports	Injuries were directly related to the higher workload of players.	Weekly updates should be done on professional players to monitor high workloads.	Previous injuries can lead to newer ones; context must be considered with data to understand impact of older injuries.
(Tedesco et al., 2020)	IMUs	Practitioners could determine the difference between those who had ACL surgery and those who had not.	Use IMUs to monitor those with previous ACL surgeries to mitigate further injuries.	Data was only gathered in a lab using a treadmill. Tests still need to be conducted to understand real-world validity and reliability.

Table 5. Summary of findings, recommendations, and limitations for wearable use in rugby data analysis

		Data Analysis		
Citation	**Wearables**	**Findings**	**Recommendations**	**Limitations**
(Buchheit et al., 2014)	SPI-proX™, SPI-prxX2™	Even with the same manufacturing chip version, the acceleration and deceleration varied between the devices.	Comparing two devices that are similar but have different upgrades show how data can be changed just by using a different device.	Upgrading a device might have a significant impact on the data. When comparing to previous data, the users should be weary due to the change.
(Chambers et al., 2019a)	Catapult OptimEye S5™	During the training set, the first two rows were accurate, but during the testing, the last two rows were accurate in detecting scrummages.	The algorithm, is useful for quantifying scrummage events in a rugby elite game.	False negatives occurred in the algorithm when fewer players were present. To ensure accurate data, at least 5-8 players need to participate.
(Gastin et al., 2014)	MinimaxX S4™	The device did not accurately count the number of tackles. It worked more for the one who received the tackle than the one who performed the tackle.	Device had an overall 78% rate of classifying a tackle making it useful in non-competitive sport.	The device cannot tell the difference between a tackle or a ball issue between players. Therefore, it is not accurate enough to use in a competitive sport.

vices to quantify collision number and intensity during rugby league training sessions, achieving a strong positive correlation r (mild collisions: $r = 0.89$; moderate collisions: $r = 0.97$; heavy collisions: $r = 0.99$) with a video coded method.

The MinimaxX™ utilizes GPS and inertial measurement unit (IMU) technologies. At the time when the research was conducted, the MinimaxX™ was considered the most accurate and valid sensor for collision detection (Gabbett et al.,2010, Gabbett, 2013). While Hulin et al. (2017) did assess collisions during live league match play with high true positives (371 out of a possible 380), they only measured collision number and not intensity and reported high false positive events. Chambers et al. (2019b) were able to differentiate all ruck and tackle events in rugby union when $79.4 \pm 9.2\%$ and $81.0 \pm 9.3\%$ of random forest decision trees in an algorithm agreed with video analysis for rucks ($n = 125$) and tackles ($n = 125$), respectively. Many studies investigating collision detection reported high false positives, which are attributed to accelerometers incorrectly interpreting high-intensity accelerations and change of directions as collision events (Hulin et al., 2017). Reardon et al. (2017) investigated the manipulation of the coding of g-force thresholds acquired via Catapult S5 Optimeye™ to mitigate false positives. They found that thresholds vary positionally and should be smaller than 0.5 g to accurately identify collision events. All three mentioned studies placed devices on the upper back.

Other studies investigated collision event impact forces in rugby league live-play. Using the SPI-Pro X™ by GPSports with GPS and accelerometer units, Cummins & Orr (2015) measured impact forces as well as counts of different collisions by different positions to provide information on players' tackling profiles. The accuracy of the device in detecting events was not reported, however. McLellan et al. (2011) also used a SPI-Pro device to collect data concerning the intensity, number, and distribution of collisions during elite rugby league

match play; however, the validity of the sensor has been called into question for all the measurements (Gabbett, 2013).

Wearables have been used to assess physiological demands of performance as well. Cunniffe et al. (2009) attempted to document heart rate, locomotor activity, load, and estimated energy expenditure in addition to collision count in a competitive rugby union match. They used an SPI Elite GPS™ and Polar Electro™ heart rate monitor, and their study marked the first scientific publication to utilize GPS wearables during a live rugby union game. They accomplished their goals, but limited data existed on the accuracy of the GPS. Norris et al. (2019) used a Catapult S5™ and Polar Electro Oy™ to analyze movement characteristics, load, distance, and heart rate in a particular simulation protocol to test the validity and reproducibility of the simulation. Match simulations are useful for investigating the impact of different variables on performance, but adaptation is still necessary to mimic physiological load in competitive matches.

Rehabilitation

As injuries are an indistinguishable part of rugby, restoring optimal musculoskeletal function and rehabilitation post-injury becomes vital, especially during the early part of injury rehabilitation. Returning to the initial level of performance is difficult if the rehabilitation process is not properly followed, especially if the injury requires surgical intervention. Therefore, compliance with therapy is extremely vital if the player is to resume his pre-injury performance levels (Della Villa et al., 2020). A variety of studies have discussed the mechanisms leading to an injury, the steps required for a good recovery, and the importance of integrating wearable technology. Additionally, limitation to the integration of wearables has been reported.

To establish preventive strategies, a thorough understanding of the injury mechanism is necessary. Rugby-related injuries are inherent due to the substantial amount of body contact and physical collisions taking place. Accident avoidance may not be possible due to continuous physical collisions such as tackling (Hoskins et al., 2006). This presents an opportunity for wearable technology. Thus, Li et al. (2020) conducted a study on wearable sensors' use in determining correlation between the workload and injury in American football for rehabilitation purposes. In a case-controlled study, the paper recorded workloads throughout the season's practice sessions using wearable integrated GPS tracking sensors and accelerometers (Li et al., 2020). Season-long soft tissue injuries were recorded with emphasis on data from weeks with recorded injuries. Subgroup research was also carried out to assess whether the reported results were confounded by the training duration and type of injury. Generally, the experiment's results showed the important role of GPS-based sensors in detecting injuries; calculations proved that injuries were related to an increase in training load a month prior to that injury. This data collection is significant, especially for rehabilitation. These findings suggest a continuous and individualized monitoring of training loads of professional rugby players to ensure a smooth rehabilitation process.

Coughlan et al. (2011) deployed GPS-based wearable technology analysis for evaluation of training demands on rugby players. The study provided details of data retrieved from the GPS sensor and concluded that, when combined with game video footage, the data aids medical teams in understanding the injury mechanisms. The integration of wearable technology was and remains important in developing recovery programs that carefully challenge an injured player to adjust to the games' demands before resuming competition (Coughlan et al., 2011). In addition to the other injuries already discussed, the study by Tedesco et al. (2020) discussed the return for players who injured their anterior cruciate ligament (ACL). ACL injuries are frequent with a considerable percentage of players who are not able to return to competitive heights. Subsequently, return to sport after ACL reconstruction remains a huge challenge for clinicians. Therefore, the authors suggest wearable sensors as a potential solution for monitoring returning players (Tedesco et al., 2020). The proposed machine learning helps investigate how worn inertial sensors distinguish between healthy and post-ACL rugby players. Genuinely, the data from wearable sensors help build learning approaches to better understand how a full return is possible. Thus, based on the learning model and error patterns identification, a full rehabilitation program can be deduced.

However, there remains limitations to the accuracy and reliability of wearable sensors used in such cases (Howe et al., 2020). Most experiments are in-doors or inside a lab-controlled setup in addition to lack of various important parameters and variables that are needed to build concrete conclusions. Despite the existence of numerous studies that considered applying inertial sensors for rehabilitation, there is still a shortage of experiments that can reliably and consistently evaluate athletes' performance using wearable technology during rehabilitation and after return to sport.

Data Analysis

Data analysis is the backbone of wearable applications and allows information recorded by these sensors to be quantified and qualified as accurate and reliable. However, Düking et al. (2018) found that despite the rapid and widespread adoption of wearables, there is a lack in standardized evaluation of this data in a trustworthy manner. Many university athletic departments are overwhelmed by the data and are teaming up with academic departments to aid in the process of validating and analyzing such data (Luczak et al., 2020).

At the lowest level, the sensors are made by different manufacturers with different testing methods (Düking et al., 2018). The sampling frequency of a sensor is a predominant issue in preserving the quality of the data collected, since sports with varying levels of intensities require higher sampling frequencies to avoid aliasing (Düking et al., 2016). Rugby, with its higher intermittent intensity, requires a higher sampling frequency to present useful data (Chambers et al., 2019). The sampling frequencies typically used for a GPS device is 10Hz and 100 Hz for an accelerometer device. As such, one of the recommendations proposed by Düking et al. (2018) is for manufacturers of wearable sensors to arrange independent scientific evaluation of sensors. One evaluation was performed by Gastin et al. (2014) for a MinimaxX™ microsensor composed of an accelerometer and gyroscope package coupled with a

proprietary tackle detection algorithm. This study found that of 352 tackles observed, only 78% were correctly identified by the manufacturer's software, with prediction predominantly reliant on tackle intensity (Gastin et al., 2014). This study shows the limitations of a universal approach to wearable technology and suggests that more robust sport-specific algorithms will need to be developed.

Stringent data analysis of new wearable technology is necessary before widespread adoption, but even the best experiments have inherent deviations. Düking et al. (2018) proposed the standardization of reliability, sensitivity, and validity measurement methods. To improve reliability of measurements across studies, Düking et al. (2018) suggests that the intra-subject reliability should be measured in standard deviation with coefficient of variation reported. Another suggestion to improve reliability is to assess systematic bias because of proper pre-measurement training and fatigue levels throughout the study (Düking et al., 2018). Furthermore, random variations can be reduced through larger participation pools (Düking et al., 2018). Intraclass correlation can be used to assess the test and retest reliability to show how differing trials compare to each other (Shrout & Fleiss, 1979). Similarly, inter-device reliability could be determined to understand the changes of data provided by different wearables using the coefficient of variation (Buchheit et al., 2014). The sensitivity of the sensor can also greatly impact data analysis (Čović et al., 2016). As such, sensors must be sensitive enough to detect the smallest worthwhile change while isolating unwanted readings from non-worthwhile movements (Čović et al., 2016). To assess the validity of the measurements, Düking et al. (2018) suggests that once the criteria measured is assessed for reliability, then linear regression is performed to identify bias followed by Pearson's product-moment correlation to measure the strength and direction of the data and wearable correlation.

Limitations

As with any narrative review, the intent of this study is to provide a high-level overview of the current state-of-the-art so that practitioners will have a single document from which to make informed assessments of technology solutions and the corresponding use cases. This study is not intended to reflect upon every rugby- and technology-based study in detail and therefore some research papers will be left out for the inclusion/exclusion criteria reasons demonstrated in Figure 1. Also, this study only includes peer-reviewed research; therefore, some rugby teams and rugby coaching professionals may have unique uses for technology not listed in this narrative review. Likewise, other athletic programs outside of the sport of rugby may be using sensor-based wearables to assess rehabilitation and other metrics that would apply to rugby but wouldn't have been included in this study as well.

Practical Implications

As the wearable market grows into a $20 billion dollar industry in 2022 (Luczak et al., 2020), new strength and conditioning coaches entering the rugby space will want to align themselves with the technologies that provide the most value based on the data they need to capture about their athletes. This study provides that initial technology review of use cases so that practitioners in the field can quickly identify options that most align with their needs. As wearables continue to advance and new products are introduced, this study will remain relevant because the core technology-usage relationship will still apply despite new companies, new labeling, and other interactive improvements upon the core sensor types. Further, while this study is specifically written to address the technology questions of those in the sport of rugby, all other field-based sports such as American football, soccer, lacrosse, and others may benefit from the same information provided herein. The tasks within other sports may differ compared to rugby, but the attributes of playing fields and the basic biomechanics and physiologies of the human body will largely remain unchanged between sports.

CONCLUSION

The established use of wearable technology in elite rugby has facilitated the measurement of a broad range of data. GPS-based wearables are utilized more compared to other devices described in the reviewed literature that were not location-based. Wearables are useful in supporting player and practitioner efforts to promote health and ensure peak performance before a game. Wearables may also be used in player performance to determine injury severity and mitigation strategies as well as monitor collisions and develop positional activity profiles. Post-match, wearables can be utilized to monitor muscle stimulation, player recovery process, and overtraining. Finally, the data collected through wearable technology may enhance conditioning programs by enabling the tracking of numerous aspects of performance such that players can meet the demands of competitive match play safely. Future research is warranted for standardized evaluation of player game and training data and development of soft-tissue injury prediction models.

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