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Review

Innovative Use of Wrist-Worn Wearable Devices in the Sports Domain: A Systematic Review

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Abstract: Wrist wearables are becoming more and more popular, and its use is widespread in sports, both professional and amateur. However, at present, they do not seem to exploit all their potential. The objective of this study is to explore innovative proposals for the use of wearable wrist technology in the field of sports, to understand its potential and identify new challenges and lines of future research related to this technology. A systematic review of the scientific literature, collected in 4 major repositories, was carried out to locate research initiatives where wrist wearables were introduced to address some sports-related challenges. Those works that were limited to evaluating sensor performance in sports activities and those in which wrist wearable devices did not play a significant role were excluded. 26 articles were eventually selected for full-text analysis that discuss the introduction of wrist-worn wearables to address some innovative use in the sports field. This study showcases relevant proposals in 10 different sports. The research initiatives identified are oriented to the use of wearable wrist technology (i) for the comprehensive monitoring of sportspeople's behavior in activities not supported by the vendors, (ii) to identify specific types of movements or actions in specific sports, and (iii) to prevent injuries. There are, however, open issues that should be tackled in the future, such as the incorporation of these devices in sports activities not currently addressed, or the provision of specific recommendation services for sport practitioners.

Keywords: wrist-worn wearables; smartwatches; smartbands; activity trackers; sports; sensors

1. Introduction

Crabtree and Rhodes [1] defined in 1998 a wearable device as *"a computer that is always with you, is comfortable and easy to keep and use, and is as unobtrusive as clothing"*. The media present wearable technology as a disruptive technology, which will be a major player in the consumer electronics market. Indeed, according to the Statista portal [2], the wearable market grew from 28.8M units sold in 2014 to 222.9M expected to be sold in 2019, and 302.3M units in 2023 (forecasts as of June 2019). It should be mentioned that most sales correspond to wearable wrist devices.

The definition of the term wearable encompasses different kinds of devices, from the ones that are placed on the feet, such as shoes that include motion sensors, to devices that are placed on the head, such as smart glasses or caps that detect drowsiness and alert drivers [3], going through devices that are placed on any other part of the body halfway. However, the devices that are really succeeding in the consumer market are smartwatches and smartbands, i.e., wearables that are placed on the wrists of their owners. Figure 1 summarizes the number of wearables sold in 2018, together with an estimation of sales in 2022, about several types of wearable devices (data from International Data Corporation Worldwide Quarterly Wearable Device Tracker [4]). As the figure depicts, a very high percentage of the sales, 87.5% (166.6M), corresponds to wrist-worn wearables (i.e., smartwatches and wristbands), while the rest (clothing, earwear, modular and others) represent only a 12.5% (23.7M) of the shipments.

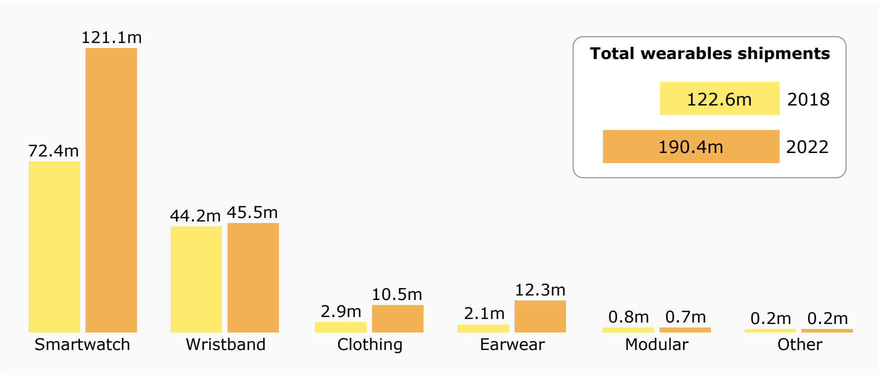

Figure 1. Estimated worldwide wearable device shipments (in millions units).

In the last five years, wrist wearables have become popular in the form of smartwatches, smartbands or activity trackers. To a large extent, this popularization is supported by the use of these devices as non-intrusive data collection elements for monitoring sports or fitness activities, mainly running activities and, to a lesser extent, activities related to swimming or cycling.

These devices include sensors, in most cases in direct contact with the skin of the user, which support the gathering of information of great potential for monitoring, managing and improving sports practice, such as position indicators, accelerometers, gyroscopes, magnetometers, heart rate sensors, or even, although less frequently, sensors to capture skin temperature, maximal oxygen consumption (VO_2 max) or galvanic skin response (GSR), among others. Thus, manufacturers such as Polar, Garmin, Fitbit or Suunto, and major technology companies such as Apple, Samsung or Google, offer solutions based on this type of devices for both professional sportspeople and amateur athletes, and even sporadic practitioners.

However, the features provided by the devices presently available in the market are usually limited in terms of functionality, and are available for a limited number of activities such as running, cycling or swimming. Please note that the data collected by the sensors in these devices have great potential for the monitoring of many different aspects related to a broad range of sports, and even beyond the sports field. While it is true that several studies showed reasonably good accuracy or precision [5] of the sensors incorporated in consumer wearables, others argue that these parameters are not sufficiently high under certain conditions of use, such as intensive exercise [6,7]. This, however was not an obstacle for the scientific community to address this technology and propose the use of wrist wearables in different areas. Thus, we can find proposals in the medical/health field [8–10], in the workplace [11], the military [12], the recreational sector [13], or the educational domain [14,15].

This work is aimed at identifying existing research proposals for the use of wrist wearables in the sports field. These proposals have to be innovative and explore solutions beyond the ones available in the market, i.e., they should unleash the full potential of data collected by smartwatches and smartbands. Thus, the research question posed is the following:

What proposals for innovative use of wrist-worn wearable devices currently exist addressing the sports field?

To answer this question, the scientific literature was surveyed to identify articles published along the last five years that, directly or indirectly, discuss novel research targeted at the introduction of wrist wearables to meet needs or demands in the sports field. The analysis of these works will would us to provide an answer to the research question posed, and to discover in which sports proposals are being made, what type of devices are being used, and what processing is carried out on the data collected by these devices to create innovative solutions or services. This study would ultimately serve to highlight the potential of wearable wrist devices in the sports field, to detect existing gaps, and to provide a foundation for new lines of research in this domain.

Section 2 of this manuscript discusses the methodology and tools applied to identify the relevant scientific literature to answer the research question posed. Section 3 describes the results of applying this methodology, namely the identification of 26 relevant articles fulfilling the requirements established in Section 2. Section 4 discusses the analysis of the articles selected. Finally, Section 5 offers the conclusions drawn from this systematic review.

2. Materials and Methods

To answer the research question raised, a systematic review of the scientific literature was performed. This review was driven by the general principles of the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) [16].

2.1. Search Strategy

The following databases were used to perform the search process corresponding to the inception up phase of PRISMA in August, 2019: Scopus, MEDLINE, Web of Science (WoS) and ProQuest. The objective of the search was to locate studies that (1) used a wearable device equipped with sensors, either a commercial device or a device developed ad hoc. Although the main focus of this research is on commercial wearables, the works referring to ad hoc devices were also considered as evidence of the potential of this technology, no matter it was not still transferred to the market. Another selection criterium was that (2) the device used was designed to be worn on the wrist, although wearables placed on the lower part of the arm were also considered because, as in the previous case, they also serve to highlight the potential of wrist devices. Finally, (3) the wearable should be used to support or implement some service or functionality in the sports field.

According to the aforementioned search requirements, the standard query consisted of three blocks of terms, one for each condition above, linked by logical AND operators. Within each block, terms related to the search condition are linked by logical OR operators:

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(sensor OR wearable OR smartwatch OR smart watch OR smartband OR smart band)
AND
(wrist* OR arm* OR bracelet)
AND
(sport* OR fitness OR gym* OR exercise OR athlet* OR training OR workout OR physical
activity)
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The asterisk (*) after a word stem expands the search to include all terms beginning with that stem.

Works published in reference journals after January 1, 2015 were considered. Query results from the databases considered were uploaded to Mendeley.

An informal search in external sources was also conducted. In particular, works available on Google Scholar were investigated, and also some recently published surveys related to the use of wearables [17,18]. The outcomes of this process were also incorporated to Mendeley.

2.2. Eligibility Criteria

Only articles written in English and published along the last 5 years in prestigious peer-reviewed journals of international scope that were relevant to respond to the research question were considered. Papers were discarded that:

1. Were not explicitly focused on sports issues.
2. Used devices that cannot be considered wearable devices.

3. Did not use a wrist wearable in a way that was instrumental to complete the research discussed.
4. Were only aimed at verifying the reliability or accuracy of a sensor under certain conditions, even if these conditions were related to the sports realm.
5. Were focused on proposing some algorithm to improve the accuracy or reliability of the data obtained using some sensor in certain conditions, even in a sports environment.

2.3. Selection Process

Using the functionalities of the Mendeley software, duplicate references were identified and deleted. In a first screening phase, the resulting set of references was classified into 4 groups that were assigned to 4 of the authors (J.M.S.-G., S.V.-R., M.R.-M. and L.M.Á.-S.). Based on the information contained in the title and abstract, the reviewers assessed the relevance of each of the papers to the research question, labeling each reference according to a scale of potential relevance with 6 levels ranging from 0 (i.e., the work is not at all relevant) to 5 (i.e., the work is relevant without hesitation). Those works scoring at least 3 were selected for further eligibility analysis.

In the eligibility phase, works scoring 5 in the screening phase were selected for the final meta-analysis phase. Each of the papers scoring 4 or 3 in the screening phase were assigned to 2 of the authors to be assessed independently. Upon reading the full text, each reviewer decided whether the work was relevant or should be discarded for incurring in any of the exclusion criteria, in which case the reviewer should indicate the reason for exclusion. Disagreements were resolved among all the authors through further discussion.

3. Results

The objective of this work was to carry out a systematic review, according to the PRISMA methodology, to analyze and combine the results of independent studies about innovative uses for wearable wrist technology in the field of sports. As shown in Figure 2, during the searching phase, 1887 articles in the target databases and 4 additional works in external sources were identified, 3 in surveys related to portable devices and 1 contribution to a conference found in Google Scholar using a query similar to the original one. After duplicate removal, 1043 papers were title and abstract-screened by the authors, who graded them with a value between 0 and 5 according to their relevance. 524 papers scored 0; 246 got a score of 1;166 a 2; 66 scored a 3; 32 a 4, and finally 12 works received a score of 5.

The 12 top articles were checked again by the authors and selected directly for analysis. The 98 papers labeled with a 3 or 4 passed to the eligibility phase. In this phase, two of the authors independently assessed their eligibility and decided whether they should pass to meta-analysis or not. Discrepancies were resolved by consensus among the six authors. 84 articles were discarded and labeled with their corresponding exclusion criteria (cf. Section 2.2). Most of the papers discarded (51 articles) were so because they were not directly oriented to sports activities. Typically, they were articles that propose or study techniques for the recognition and classification of daily activities (e.g., [19–22]). Although some of these activities could be related to sports, such as running, research was not focused on the sports field. A considerable number of jobs (30 articles) were also labeled as ”not focused on wrist devices” (e.g., [23–26]), since the wearable device used was not intended to be worn on the wrist or forearm, or because a wearable wrist device was used, but it had little significance when additional wearables were used in other parts of the body or in the equipment used in sports. 26 articles were labeled for exclusion either because they were focused on analyzing the performance of a sensor (13 articles) (e.g., [27–30]) or because they were oriented to propose some algorithm for improving the performance of a heart rate sensor (13 articles) (e.g., [31–33]). These articles did not really propose any new service or functionality in the sports field beyond the improvement of the accuracy or protocols of the devices themselves, no matter this may occur in a sports context, in which some sensors may be affected by the abrupt movements in that context. Finally, 4 articles were discarded because the device used could not really be classified as wearable (e.g., [34,35]), and 4 more articles for other reasons.

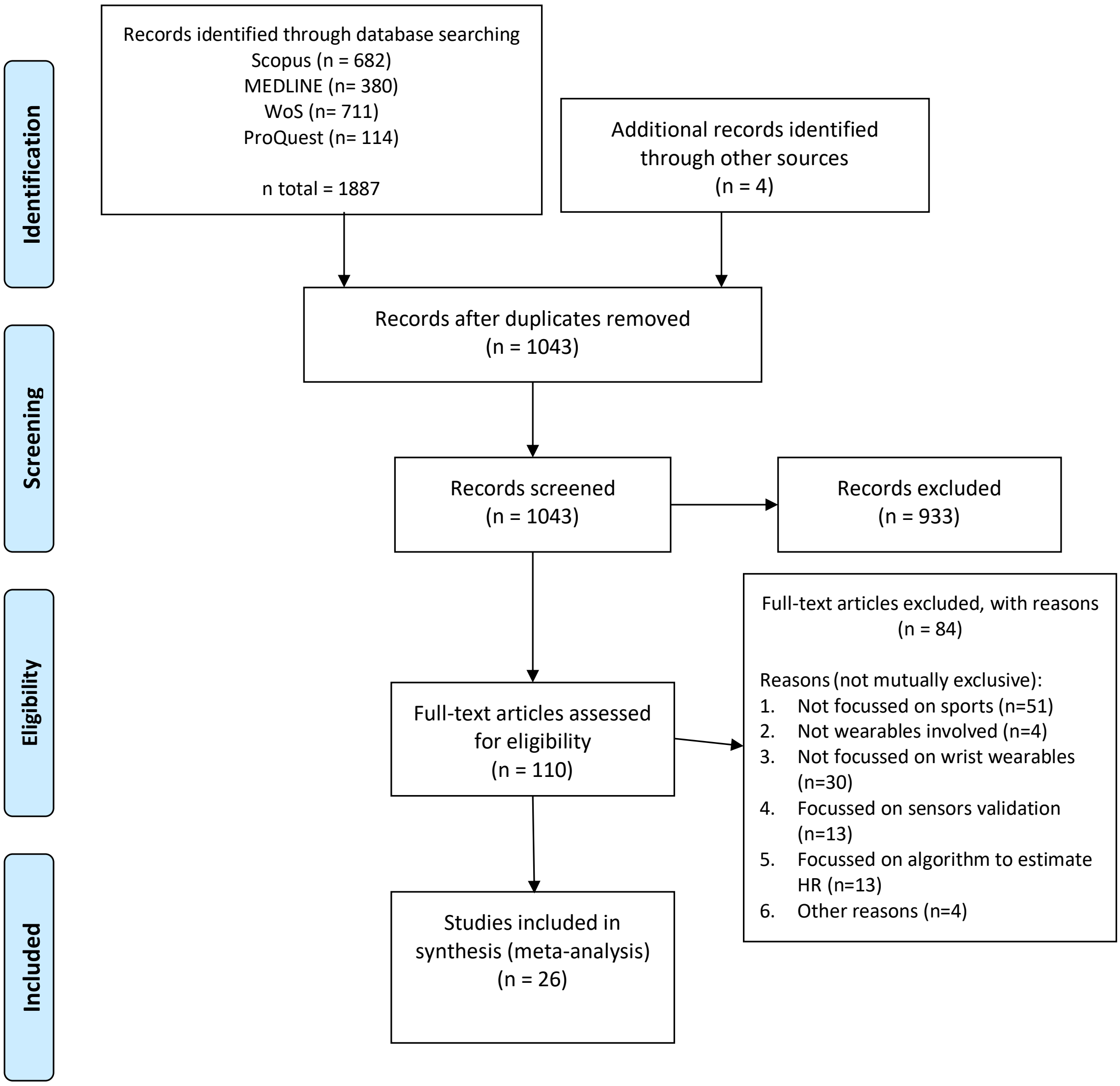

Figure 2. Flow diagram of the systematic review according to PRISMA guidelines.

Eventually, 26 articles were selected to be thoroughly analyzed by the authors, focusing primarily on extracting information on: (1) the use of the portable wrist device in order to obtain an innovative service or functionality in the sports field; (2) the particular device used, whether there was a device developed on purpose for the research carried out, or a commercial-off-the-self device, and the sensors in that device; (3) the sport or sports to which the proposed service or functionality is targeted; (4) the analysis techniques used for the development of the service or functionality; and (5) the validation protocol carried out. Table 1 briefly summarizes the outcomes of the synthesis (meta-analysis) on each of the articles that passed the eligibility phase. This table is intended to serve as a tool to identify the key concepts of the contributions surveyed, and to provide a starting point for researchers focused on the application of wrist wearables in the field of sports.

Table 1. Synthesis of the studies.

Reference	Innovative Use	Device	Sport	Analysis Techniques	Validation
Maijers et al. [36] (2018)	The feasibility of using a commercial wrist wearable was studied to monitor daily physical activity and automatically track training sessions of wheelchair athletes using data not intended for this type of users (e.g., step count).	Fitbit Charge 2, and more specifically, information obtained from the pedometer and the heart rate sensor.	Handcycling	Ad-hoc data processing is not performed. The dashboard graphics provided by Fitbit are directly used.	Tested with 6 participants in the HandbikeBattle race, an annual trial for handcyclists, for periods between 2 weeks and 9 months. The validation of the proposal is informal and descriptive.
Margarito et al. [37] (2015)	In this study, a user-independent algorithm is proposed to identify sport activities from the accelerometer data extracted from a wrist wearable. The sports considered are: cycling, cross training, rowing, running, squatting, stepping, walking and weight lifting.	Philips DirectLife activity tracker. Data generated by a triaxial accelerometer ($\pm$2 g, 20 Hz) is used.	Generic	Template acceleration signals are generated for each supported sport (template generation) and the similarity of the current signal is calculated with the template signals (template matching) to perform classification.	Tests performed with 29 subjects with normal weight and 19 with overweight. A true negative rate (TNR) greater than 90 % and added sensitivity (considering all sports) of 74.7 % for normal weight and 78.7 % for overweight subjects were obtained.
Balsalobre et al. [38] (2017)	The feasibility and reliability of using a commercial-off-the-shelf wearable to measure the speed of the barbell in several resistance training exercises was researched, namely full-squat, bench-press and hip-thrust.	Beast Sensor, a commercial wearable specific for weight training with accelerometer, gyroscope and compass.	Powerlifting (full-squat, bench-press, hip-thrust)	The Beast Sensor data collection app provided speed, so ad hoc processing is not performed to obtain this variable.	10 powerlifters performed 6 sets of incremental exercises. Barbell velocity was simultaneously measured using a linear transducer (gold standard), two Beast Sensors (on the subjects' wrist and on the barbell) and the iOS PowerLift app. High reliability is obtained, although with some bias in the average.

Table 1. *Cont.*

Reference	Innovative Use	Device	Sport	Analysis Techniques	Validation
Spratford et al. [39] (2015)	An ac-hoc wearable placed on the wrist was used to measure the peak outward acceleration (POA) of a ball at the end point of a bowling action in cricket. This variable is a key element when assessing the illegality of bowling.	Ad-hoc wearable with 2 accelerometers and a gyroscope. Only one ADXL190 accelerometer (±100 g, 200 Hz) was used.	Cricket	Data collected to compute POA are compared with those collected using a validated motional analysis ball release (MABR) protocol (based on high-speed video capture). The correlation between both data is analyzed.	148 deliveries were monitored from 21 professional bowlers. A high correlation between the computed POA from the wearable data is verified with the measurement obtained by MABR, regardless of the delivery type and elbow anthropometry.
Camp et al. [40] (2017)	Data from a wearable was used to support the modelling of the relationship between elbow varus torque and arm slot and arm rotation in baseball pitchers. The goal is to identify modifiable factors that may potentially reduce the stress experienced by the elbow.	motusBASEBALL, commercial compression sleeve equipped with an IMU.	Baseball	Linear mixed-effects models and likelihood ratio tests were used to estimate the within-subject relationship between elbow varus torque and arm slot, arm speed and arm rotation.	81 professional pitchers performed 82,000 throws while wearing a motusBASEBALL.
Stiles V.H. [41] (2018)	Study aimed at demonstrating the validity of several open-source metrics obtained from the analysis of data from wrist-worn accelerometers in runners, with the objective of discriminating between running/nonrunning training days and quantify training load on training days.	GENEActiv accelerometer, a commercial research-oriented smartband (±8 g, 100 Hz).	Running	Receiver operating characteristic (ROC) analysis was applied to accelerometer metrics to discriminate between running and nonrunning days. Variance explained in training log criterion metrics was examined using linear regression with leave-one-out cross-validation.	Accelerometer data obtained from 35 experienced runners over 9 to 18 weeks were date-matched with self-reported training log data. A total of 1494 accelerometer days with at least 10 hours of wear per day were analyzed.

Table 1. *Cont.*

Reference	Innovative Use	Device	Sport	Analysis Techniques	Validation
Rawashdeh et al. [42] (2016)	This work describes a proposal to detect movements and activities that are likely to cause shoulder injuries. It focuses on the types of specific movements that, during sport practice, make intensive use of the shoulder.	Ad-hoc wearable with a 3-axis accelerometer (ADXL345), 3-axis gyroscope (ITG-3200 MEMS) and 3-axis magnetometer (HMC5883L)	Baseball/ volleybal	Preprocessing based on the AHRS algorithm is applied. Descriptive statistics are used on the captured data, signal processing (FFT) to detect that the upper limb was elevated, and a Decision Tree Classifier to measure the overuse of the arm.	Tests carried out with 11 subjects who performed 7 shoulder movement exercises and 2 sports activities: baseball throw (99 valid repetitions) and volleyball serve (103 valid repetitions).
Wang et al. [43] (2018)	The innovative use of this research is to detect the level of a volleyball player. 3 levels of play are considered, namely amateur, sub-elite and elite. Detection is done using players' spikes.	Ad-hoc wearable using an MPU9250 unit. 3-axis acelerometer ($\pm$16 g) and 3-axis gyroscope.	Volleyball	SVM, SVM + PCA, k-NN and Naive Bayes machine learning (ML) techniques are used to develop the classifier. Supervised training is performed using images taken with a high speed camera. Manual processing of these images.	The tests carried out with 10 right-handed men (3 amateurs, 3 sub-elite and 4 elite). 120 spiking trials were performed. Average accuracy of 94%.
Margarito et al. [37] (2015)	This research develops a system to monitor lactic acid secretion on the surface of the skin. The innovation is to make a sensor that can monitor lactic acid secretions while exercising.	Ad-hoc sensor. The system combines a biosensor using LOD and osmium wired HRP (Os-HRP) reaction system with a microflow-cell.	Generic	The measurement of the changes in the sensor is performed with an ammeter. During exercise, heart rate is also monitored (9722B-FS from Adidas). The relationship between intensity, segregated lactic acid, potential applied to the sensor, exercise intensity and heart rate is represented by graphs.	Tested with 1 user who was subjected to exercise of variable intensity using an exercise bike. A correlation between the sensor measurements and the intensity of the exercise was confirmed.

Table 1. *Cont.*

Reference	Innovative Use	Device	Sport	Analysis Techniques	Validation
Kölling et al. [44] (2016)	This study carries out an innovative analysis of the effect that high-intensity training (HIT) sports practice has on sleep parameters. Sleep quality is measured objectively using a wearable, and subjectively by means of standardized questionnaires.	Commercial SenseWear ArmbandTM wearable. This device has a 2-axis acelerometer, skin temperature sensor, galvanic skin response sensor, and heat flux sensor.	Generic (HIT training)	Statistical analysis is carried out using descriptive statistics and ANOVA on quality-of-sleep data provided by the wearable. "Subjective sleep rating" and "Recovery-Stress Questionnaire for Athletes" questionnaires are used for subjective assessment.	The sleep of 42 athletes was monitored. These were classified into 2 groups of 21 subjects. One of the groups performed high-intensity training for 14 days and the other served as a control group.
Burns et al. [45] (2019)	This work uses wrist-worn wearables to monitor step frecuency (SF) and SF variability of participants in the 2016 100-km World Championship. SF variations are studied with respect to speed, distance run, height, age, weight or previous experience.	Commercial wearables suitable for running practice (Garmin, Suunto and Polar). Accelerometer data is used to detect steps.	Running	A descriptive statistics analysis is performed to compare different parameters with SF data. Comparative graphs are provided and linear regression tests are computed in some cases.	The data captured by the 20 best participants who monitored themselves using their own wrist bands were used.
Salman et al. [46] (2017)	The innovative application discussed in this work consists of to detect when a bowling action in cricket is legal or not by using data from inertial sensors in a wrist-worn wearable.	Ad-hoc wearable with a 3-axis accelerometer and a 3-axis gyroscope.	Cricket	The classifier is developed using different ML techniques: SVM, k-NN, Naïve Bayes, RF and ANN. Supervised training is performed using the opinion of cricket experts as a reference.	Tested with 14 male players between 15 and 30 years old. Series of legal and illegal bowls were made.

Table 1. *Cont*.

Reference	Innovative Use	Device	Sport	Analysis Techniques	Validation
Kos and Kramberger [47] (2017)	This work successfully explores the possibility of using ad hoc wearables to detect the impact of the racket against the ball and estimate the type of shot made. This information is the result of processing raw data from the sensors.	Ad-hoc weareable device including a 3D gyro, 3D accelerometer (±16 g), a heart rate sensor, and temperature sensor.	Tennis	The shot is identified by means of a two-point derivative of the acceleration curves. The identification of the type of stroke is based on the rotation accelerations in a temporal window around the hit moment.	446 strokes from 7 different tennis players.
Mangiarotti et al. [48] (2019)	Using custom made devices, authors attempt to get a real-time system to identify game actions in basketball (pass, shot and dribbling) by analysing data related to accelerations.	Ad-hoc wearable device with a MIMU sensor and a Bluetooth module.	Basketball	Implementation of k-NN and SVM in MATLAB for the detection of target game actions.	Not specified.
Wells et al. [49] (2019)	MIMU sensors are applied to cricket actions in an attempt to measure and monitor these actions without the support of motion capture systems.	Commercial wearable Xsens MTv Awinda MIMU sensors.	Cricket	Measurements from the proposed model are just compared with the gold standard.	Nine injury-free participants attending a single test session each.
Whiteside et al. [50] (2017)	The authors explore how data obtained with wrist-wearable sensors can be used to automatically classify shot types in tennis by means of different ML algorithms.	Commercial wearable from IMeasureU involving a 500 Hz 9-axis IMU.	Tennis	A custom MATLAB script was developed to process accelerometer and gyroscope data. Information obtained and annotated was used to train and test 6 types of learning classifiers (support vector machine (SVM), discriminant analysis, random forest (RF), k-nearest neighbor (k-NN), classification tree, and artificial neural networks (ANN)).	66 training sessions involving 19 athletes.

Table 1. *Cont.*

Reference	Innovative Use	Device	Sport	Analysis Techniques	Validation
Bergamini et al. [51] (2015)	Information obtained from regular wrist-wearable devices on handcycling athletes is used to evaluate the effectiveness of specific training routines in wheelchair with bio-mechanical propulsion. The devices involved are intended to be used for walking or running.	Commercial wearable from Opal (APDM Inc.) involving IMUs.	Handcycling	Descriptive statistical analysis using SPSS.	Twelve junior wheelchair basketball players distributed into 2 groups (control and experimentation) carried out three experimental sessions where measurements were completed.
Makhni et al. [52] (2018)	Information from sensing devices (accelerations and changes in orientation) worn by baseball pitchers is used to try to identify the type of launch made.	Commercial device including a gyroscopic sensor with an accelerometer from Motus Global.	Baseball	Classification system based on general linear models implemented using R.	37 players took part in the experiment, completing 24 pitches each.
Okoroha et al. [53] (2018)	Off-the-shelf devices are used to assess valid predictors of torque across the medial elbow for baseball pithcers' injuries.	Commercial device including a gyroscopic sensor with an accelerometer from Motus Global.	Baseball	Basic descriptive statistics. Tukey-Kramer fit and Mixed Models—Repeated Measures were applied.	20 young baseball pitchers were instructed to throw 8 fastballs, 8 curveballs, and 8 changeups in a standardized but randomized sequence over a 25-min period.
Ma et al. [54] (2018)	A full custom wearable is applied to implement a system capable of identifying 9 characteristic basketball movements using just acceleration and rotational speed without the support of further sensing devices.	Ad-hoc device with a MIMU sensor.	Basketball	ANN implemented in MATLAB.	Not specified.

Table 1. *Cont.*

Reference	Innovative Use	Device	Sport	Analysis Techniques	Validation
Bai et al. [55] (2016)	Commercial smartbands are used to deploy a system for the automatic identification of shooting actions from basketball players. This feature requires an advanced data processing and goes beyond the capabilities provided by the manufacturer of the bands used.	Microsoft Band.	Basketball	Basic statistical values are generated from the downloaded data, followed by a two-stage processing: first, a RF is applied and then a collaborative classifier.	2 one-to-one basketball games (20 min of playing time in total).
Parak et al. [56] (2017)	This research proposes an innovative approach to estimate heart rate, energy expenditure and maximal oxygen outtake (VO_2 max) while running using an optical heart rate sensor from a basic commercial wearable.	Commercial wearables suitable for running practice. PulseOn to measure heart rate, and a Samsung Galaxy S3 smartphone for geolocation.	Running	An analysis with descriptive statistics is performed, and basic parameters are computed (e.g., mean and standard deviation), as well as some comparative analysis tests (e.g., Wilcoxon test, paired *t*-test, etc.). A chest band and respiratory analysis used as gold standard.	Tested with a sample of 24 healthy adults running outdoors and on a treadmill.
Kim et al. [57] (2017)	An ad hoc developed wearable is used to analyze the golf swing, performed with both hands, right and left. Its objective is to improve golfing technique and serve as a training tool for golfers.	Ad-hoc designed wearable, consisting of a silicone wristband, battery and MCU speed sensor. It is used a tri-axial accelerometer sensor (250 Hz).	Golf	Performs a mathematical analysis consisting of transforming the data collected from the sensor into quaternions, and modeling the swing movement through position, direction and speed of these quaternions.	A 3D model of the movement performed is generated to be compared with an average swing. Initial study. No data provided from a validation pilot.

Table 1. *Cont.*

Reference	Innovative Use	Device	Sport	Analysis Techniques	Validation
Hsu et al. [58] (2018)	Study focused on the recognition of sports and daily life activities. A wearable based on an inertial sensor network, and a recognition algorithm are used.	Ad-hoc wearable based on an inertial sensor network, composed by a microcontroller (Arduino Pro Mini, 16MHz) and a six-axis inertial sensor (MPU-6050, 100 Hz).	Generic	First, it captures and processes the microcontroller data for calibration, signal filtering and normalization. Then, it uses a ML algorithm based on SVM to classify the activities monitored with the sensor.	Validated with a sample of 13 people. Data about the correct classification rate (CCR) of activity classification is provided.
Walker et al. [59] (2016)	A system is designed to estimate energy expenditure (EE) of professional Australian football players during training and competition. It aims to improve the physical performance of players.	Commercial wearables are used: SenseWear Armband (Model MF-SW) to estimate energy expenditure; and MiniMax4.0 (Scoresby Australia), to monitor oxygen consumption.	Australian football	A descriptive statistical analysis is performed to compute basic parameters (e.g., mean and standard deviation), as well as Pearson's correlation analysis and error estimation.	Tested with a total of 18 professional Australian football players, during training, competition, and non-exercise activity thermogenesis (NEAT) sessions.

Table 1. *Cont.*

Reference	Innovative Use	Device	Sport	Analysis Techniques	Validation
Soltani et al. [60] (2019)	Study aimed at accurately estimate gait speed during outdoor exercise (walking and running) using a low-consumption wrist wearable device.	Commercial wearables suited for running practice: wirst-worn inertial sensors (Physilog® IV, GaitUp, CH), and a head-worn Global Navigation Satellite System (GNSS) device as a location reference.	Running	A descriptive statistical analysis is performed to compute basic parameters (e.g., mean and standard deviation), as well as a Kruskal–Wallis test and a Spearman correlation for comparative analysis. ML algorithms are also applied to predict wrist movement-related parameters (e.g., energy, periodicity, posture, etc.).	Tested with a total of 30 volunteers who run and walked during 90 min outdoors.

4. Discussion

4.1. Innovative Uses of Wrist-Worn Wearables

The analysis of the literature indicates that the innovative uses given to wrist wearables in the sports field are mostly focused on four broad areas: (i) monitoring of sports activities, (ii) identification and classification of sports activities, (iii) performance improvement and (iv) injury prevention. Table 2 provides a classification of the studies identified in the four areas mentioned, according to their main objectives. These four purposes are neither exclusive nor fully independent, that is, some of the articles address aspects related to more than one purpose. Eventually, a basic purpose common to all studies can be established, namely the unleashing of the information that can be obtained from the wearable sensors to offer added-value information or services.

Table 2. Classification of the works analyzed according to their purpose.

Aim		# Studies	References
Monitoring of sports activities	Sportsperson's physiological or biological variables	5	[47,56,59–61]
	Sportsperson's behaviour	2	[41,45]
	Other elements beyond sportsperson	2	[38,39]
	Training tracking	1	[36]
Identification and classification of sports activities	Several sports	3	[37,52,58]
	Single sport	8	[41,46–50,54,55]
Performance improvement	Impact evaluation of training for the sportsperson	2	[44,51]
	Identification of technical improvement	3	[43,57,59]
Injury prevention		3	[40,42,53]

As can be observed in Table 2, 11 papers (42.3%) focus on the monitoring of sports activities. In many cases ([47,56,59–61]), monitoring consists of measuring variables directly related to biological characteristics or the physiological state of the sportsperson (e.g., heart rate, movement, energy expenditure, oxygen consumption, gait speed or lactic acid levels). In other works ([41,45]), monitoring is designed with the objective of determining certain aspects related to athletes' behavior or identifying behavior patterns during exports activities. Ref. [45] focuses on determining step frequency patterns, while [41] seeks, among other aspects, to quantify the impact of non-sports habits occurring on the same day of a training session. Ref. [38,39] focus on the monitoring of velocity parameters. In [39], the velocity of a cricket ball is estimated, while in [38], the barbell velocity is measured for several resistance exercises. In a different line of work, Ref. [36] focuses on a mechanism for the automatic monitoring of daily physical activity during the training season, which in turn enables the automatic generation of daily training plans. It should be noted that, although in the general case the works analyzed focus on a specific sport, there are some exceptions to this fact. Ref. [61] discusses a new wearable device capable of tracking lactic acid secretions during generic sports activities, and [47] aims at the development of a device for monitoring biometric data in any sport.

Another significant number of papers (42.3%) is devoted to the identification and classification of sports activities. Within this line of work, two different areas can be identified: (i) research aimed to identify the actual sport being performed, and (ii) works devoted to identify the type of movement or activity assuming that a certain sport is being performed. Most papers focus on the second area

(30.7%), and the first objective is addressed by two papers targeting amateur athletes that want to keep a computerized record of the physical activity carried out [37], or aim to identify those days in which some activity was carried out [52]. Papers from the second area present a very good starting point for the analysis of techniques used [48,54], and for the generation of sports statistics in real time [48]. The classification of sports activities may also be focused on the detection of legal and illegal actions, as is [46], in the case of cricket. Presently, the mechanisms for detecting illegal actions can be very subjective, as they are based on the personal opinions of one or several people (e.g., the referees). In this sense, the use of wearables aims to provide objective mechanisms to replace or complement subjective ones.

Some of the works analyzed (19.2%) are targeted at the improvement of sports performance. This is an aspect that is given great relevance, especially in the case of elite athletes. The evaluation of the impact that a specific training approach has on the athlete's performance is an objective pursued by [44,51]. In particular, Ref. [51] tries to establish a monitoring protocol to evaluate the effectiveness of training plans. In a similar way, Ref. [44] includes in the analysis the study of sleep patterns and indicators, and the mutual effect between sleep quality and certain types of physical training. On the other hand, some works focus directly on the improvement of sports technique. Ref. [43] proposes a mechanism to identify the level of a player by analyzing their playing style and technique. Ref. [57] focuses on analyzing how a detailed study of games played by an athlete may help to understand and improve their technique. Ref. [59] is focused on estimating energy expenditure as an instrument for adapting training programs to individual athletes. In general, these works seem to obtain a significant advantage by analyzing the habits and techniques of athletes. Then, this information can be used to define customized training routines that directly tackle the specific weaknesses of each athlete.

The detection and prevention of injuries is another especially relevant issue. However, its presence in the literature is relatively limited (only 11.5% of the works analyze it). Injuries, especially in elite athletes, may become a most relevant challenge, with both personal and economical implications. By studying the patterns that determine their appearance, new mechanisms may be developed to help to prevent them. Elite athletes are often at the edge of their physical capabilities, which makes them more likely to suffer injuries. For example, high school athletes suffer 116,000 shoulder injuries every year [62]. Statistics such as the one just mentioned led to pass regulations to limit the activities that athletes can perform during competitions [63,64]. Among the works analyzed, Ref. [42] tries to detect those activities and movements that may cause shoulder injuries in baseball and volleyball. Ref. [40] proposes a procedure to measure and analyze the relationship between elbow varus torque and arm slot and rotation in professional baseball pitchers. Ref. [53] focuses on the prediction of injuries in youth and adolescent baseball pitchers. After the analysis of the literature, the works identified seem to agree that wearable devices are good candidates to help in the analysis of the appearance of sport-related injuries, thanks to their potential to accurately measure movement-related characteristics. In the case of wrist-wearables, these seem especially useful in injuries related to various parts of the upper limbs, and in sports that make a relevant use of them.

To sum up, according to the works analyzed, it can be concluded that the most common purposes of wearable devices in sports are related to the monitoring and classification of sports activities. In particular, those situations where movements play a relevant role are more often studied, and this occurs because movement is the main source of information provided by the most popular sensors found in wearable devices (i.e., accelerometers and gyroscopes). Despite the classification provided in Table 2, the areas identified have no clear boundaries, and in many cases links among them can be found. For example, the activity classification is closely related to the measurement of the total load supported by an athlete, which in turn is a most relevant aspect in injury prevention [50]. Similarly, doing a good monitoring of an athlete's biological and physiological variables, as well as studying their behavior, has a direct implication in performance improvement [59]. Please note that their portability and the possibility of transparent use of wrist-wearable devices facilitates the observation of an athlete during training or competition. Other observation mechanisms, such as motion tracking systems based on high-speed 3D cameras (more expensive and sophisticated than wearables), involve laboratory testing sessions, which are clearly perceived as more invasive.

4.2. Sports Introducing Wrist Wearables

An initial overview of the reviewed articles shows that four of them (15.4% of the reviewed works, Ref. [37,44,61]) are not focused on specific sports but they involve cross-cutting contributions to sports activity. The rest of the articles reviewed are clearly focused on some sport or type of sport, such as:

- Running (four papers, 15.4% of the works reviewed [41,45,56,60]). These works are aimed at obtaining relevant parameters from a sporting point of view from the physical variables monitored by wearable devices, both commercial and ad hoc, through several analytical techniques.
- Baseball (four papers, 15.4% of the works reviewed [40,42,52,53]). By using sensors placed on the upper limbs, these works focus on trying to estimate the type of movements that players perform and, from these movements, predict (and consequently try to avoid) injuries due to the explosive nature of the arm movements characteristic of this sport.
- Cricket (three papers, 11.5% of the works reviewed [39,46,49]). Wrist-worn wearables are used as decision-making support about the legality of certain actions. The applicability of certain sensors in extreme sport circumstances is also studied.
- Basketball (three papers, 11.5% of the works reviewed [48,54,55]). They seek to identify actions characteristic of the game through the use of wrist devices.
- Tennis (two papers, 7.7% of the works reviewed [47,50]). Wearable sensors are used to measureme variables that enable the identification and classification of players' strokes.
- Volleyball (two papers, 7.7% of the works reviewed [42,43]). By monitoring the game, the works analyzed pursue the classification of players according to their level of play, and the detection of potentially dangerous movements made by players.
- Handcycling (two papers, 7.7% of the works reviewed [36,51]). The practice of handcycling generates different parameters and signals from those collected during walking or running without a wheelchair. These peculiarities are used in the surveyed papers to implement recommendations on how to optimize wheelchair handling during a race, or to facilitate automatic monitoring of daily physical activity and training of wheelchair athletes.
- Australian football (one paper, 3.8% of the works reviewed [59]). The sensor measurements are used to obtain estimates of players' energy expenses, both during matches and training.
- Weight lifting (one paper, 3.8% of the works reviewed [38]). Wrist sensors facilitates the computation of repetition rates of lift-weighting exercises with different loads, and thus estimate the maximum load borne by an athlete.
- Golf (one paper, 3.8% of the works reviewed [57]). Through the data collected by sensors on the wrists of golfers, players can be advised about their playing characteristics.

From the enumeration above, it can be pointed out that popular sports are favored in the surveyed research initiatives, especially those characterized by an outstanding use of the upper limbs, i.e., those that can be directly monitored using the wearables targeted in the research question posed.

Please note that as authors of some of the contributions affirm, their works are adaptable to similar contexts. Thus, for example, works related to tennis would be applicable to badminton. This is because the models proposed do not set specific restrictions, but are based on the monitoring of movements and accelerations of the upper limbs that are, a priori, similar within the margins of state-of-the-art sensor technology.

Insofar the number of players is concerned, team sports are discussed in 15 contributions (57.7% of the reviewed works, [36,39,40,42,43,46,48,49,51–55,59]), while individual sports are targeted by 7 articles (27% of the reviewed works, [38,41,47,50,57,60]). However, it is worth mentioning that all the works studied focus on the performance of individual athletes, and do not tackle the challenge of monitoring a team as a coordinated set of players.

It should also be noted that no water, snow or air sports were addressed in the reviewed articles. This seems to be due to the fact that in these sports the number of signals to be monitored, both on the athlete's body and in other elements necessary for sports practice, require monitoring devices beyond the ones considered in this survey, i.e., wrist devices. In fact, some contributions were discarded in the later phases of article selection because the research discussed required additional sensors to those on the wrist. Examples of this are [65] where the sport targeted is skiing, and [66] that focuses on swimming. From a technical perspective, the environment in which the activity takes place poses no relevant challenge for the sensors currently available in the market, so this should not be considered a reason for not introducing wearables in such sports.

To summarize this section, we can conclude that, although it is confirmed that a remarkable range of sports activities were targeted for the introduction of wrist-worn wearable devices without requiring support from other data sources (e.g., additional sensors), there are still many popular sports in which no proposals were made. Just to mention a few, rowing in its various modalities, javelin, weight or hammer throwing, or boxing are missing, no matter all these sports make significant use of the upper limbs, and therefore they could benefit from wrist-wearable technology.

4.3. Wrist-Wearable Devices Used

With respect to the wearable devices used, they can be classified according to several criteria. A first approach would be to study which proposals selected commercial devices available in the market compared to those that use custom designs manufactured ad hoc according to the research requirements. Analyzing the contributions from that point of view, a certain balance exists between both approaches. 10 of the proposals analyzed rely on custom-designed sensors ([42,43,46–48,54,57,58,61]), while the research works referenced in [36–38,40,41,44,45,49–53,55,56,59,60] rely on standard commercial equipment available in the market.

Most of the ad hoc devices used in the latter works generally include sensors with characteristics similar to those encountered in commercial devices. Thus, a question arises as to whether not to resort directly to entirely commercial sensors, since their sensing capabilities will be similar to custom designed ones, given the obvious savings in development and testing.

A previous study by the authors [67] discussed how collecting data from commercial devices may be a complicated task, especially when trying to develop solutions that need raw or real-time data, or when solutions are sought that support devices from multiple vendors. Sometimes sellers do not provide mechanisms that allow the direct collection of the data, but provide access to already processed data stored in their datawarehouses, as with most Fitbit or Polar devices. On the other hand, the rich portfolio of different devices available in the market gives rise to different procedures for data access and information representation models. This heterogeneity among commercial devices greatly hinders the development of vendor-independent platforms.

However, despite the reasons identified above, when determining the cause of the popularity of ad hoc devices in the woks surveyed, it is not possible to be categorical. The analysis of the works does not offer clear responses, since the motivation of this fact is not always stated in the corresponding article. Besides, it must also be included among the motivating factors of this decision the intention of the authors to address the challenge of offering the same capabilities of a commercial wearable with simpler devices, i.e., with fewer sensors than those typically included in the former, or without having to resort to external manufacturers. Articles were also found whose purpose is to find out whether it is possible to perform a certain type of monitoring using ad hoc sensors compared to the mainstream commercial option [49].

From the study of the sensors included in the wearables, whether commercial or ad hoc, it can be observed that the vast majority makes a preponderant use of the information coming from magneto inertial measurement unit (MIMU) sensors. This seems to be caused by the fact that most part of the significant data used for analysis comes from acceleration readings consequence of turns and other movements made by athletes, and these sensors are the most suitable for this purpose. Of the proposals studied, only 5 (19.2% of the total, [36,44,45,56,61]) primarily use information from other sensors.

4.4. Data Collection and Processing

The comparative analysis on how data generated in wearable sensors is collected or captured in the works discussed in this review is summarized in Table 2. Three different data collection mechanisms were identified in those articles in which information about this topic is made explicit, namely via Bluetooth, through a USB connection, or by means of a memory card.

As collected in Table 3, Bluetooth is the most used method to transmit data from the wearable to the system where information will eventually be processed (14 studies, 53.85% of them). Bluetooth is a widely used solution for connecting peripheral and wireless devices to computer systems, and in this sense, all popular wearables include it. On the other hand, four works rely on a USB connection for information transfer, and another two use a removable micro SD memory card in the wearable to collect data. Finally, in the remaining seven papers the data capture protocol or procedure used is not discussed.

Table 3. Classification of works according to the way data is collected or captured.

		# Studies	References
Data collection	Bluetooth	14	[38,40,46,48–55,57–59]
	USB	2	[47,61]
	microSD	3	[39,42,43]
	NA/Other	7	[36,37,41,44,45,56,60]

According to the mechanisms just enumerated, other state-of-the-art protocols, such as NFC and ANT+ [68], are still absent in the surveyed literature. Please note that ANT+ is primarily oriented to sports and fitness sensors. Bluetooth is preferred to other options due to its wide availability and low energy consumption. However, this approach requires an intermediate device to serve as a gateway to collect the data to be transferred to the analysis environment, usually a smartphone. This is detrimental when compared to other options that would be more transparent and less invasive to the end user, such as a WiFi connection. However, the limited network availability in outdoor scenarios, where these sensors are typically used in the sports field, prevents this approach to become a preferred solution. It should be noted that the implementation of 5G connectivity most likely will overcome this situation.

Regarding the data transfers mechanisms based on USB devices and external memory cards, we believe that they are valid for development and testing environments, but they have some drawbacks to be adopted in systems with a large-scale deployment vocation, where such tasks are expected to be transparent to the end user, who ideally should not be aware about wearing a monitoring device.

Considering the data analysis mechanism referred to in the different works surveyed, we classified them according to whether a descriptive and comparative statistical analysis is performed, an analysis based on machine learning (ML) techniques, or both, as summarized in Table 3. Please note that both analysis approaches are not exclusive or totally independent. Indeed, some of the papers analyzed make use of both approaches to cover different aspects of the validation process.

Firstly, insofar statistical analysis is concerned, most of the works carry out a first analysis of basic and descriptive statistics (13 studies, 50% of them) obtaining the average values and standard deviations of the parameters evaluated in each case. Although to a lesser extent, variance and comparative studies between classes of these features are also carried out (4 studies [39,44,51,60]). The study of the correlation between features is also included, as a part of reliability validation—in-class correlation—(a total of 5 studies [37,38,56,59,60]). Additionally, four studies apply more complex statistical tests (e.g., *t*-Test, Tukey-Kramer, Wilcoxon test, Kruskal–Wallis test, etc.) [37,42,47,57], which enable a deeper study of classes or categories, especially in obtaining statistical significance. Finally, signal processing is also applied (e.g., Fast Fourier Transform, Time Series Signals, "quaternions", etc.), for specific features evaluated (e.g., heart rate, trajectory movements, etc.).

On the other hand, the use of more sophisticated analysis mechanisms in the works included in this review was also confirmed, such as the application of ML classification techniques. In Table 4 above, it can be observed that a total of 18 articles (69.23%) use these techniques, basically to classify or correctly identify the sporting task or the type of physical activity with greater granularity (e.g., cycling, cross-field training, rowing, running, squatting, stepping, walking or weightlifting in [38] to discriminate among types of weightlifting exercises). In relation to the most used classification algorithms, the most popular is the hyper-based SVM algorithm with a total of 5 works [43,46,48,50,58]; those based on close neighbors such as the k-NN algorithm, used in 4 studies [43,46,48,50]; those that rely on classification trees such as RF, which appears in three works [46,50,55]; and finally ANNs used in three studies [46,50,54]. These algorithms were applied with relevant success in other domains such as medical diagnosis [69] or stock estimation [70], and their classification potential in the field of sports practice can be reasonably expected. However, the introduction of ML approaches requires relatively large computational capacity, due to the large amount of data captured because of the high sampling rate of certain variables. High sampling rates are instrumental for a comprehensive monitoring of athlete's status and performance during sports practice. Please note that in most cases data analysis is carried out in a system different than the wearable or device where data is collected. This system, typically placed in a laboratory or in a convenient location within the sports facility, would have the required computational power to complete analysis and offer results in real time. Regarding the software tools used to carry out data processing, according to the articles where such information is provided, MATLAB is used in four studies [39,48,50,54]; SPSS is the statistical suite of choice in two works [44,51], and finally R Studio was selected in one study [52]. No work analyzed declares to use software solutions commonly used in ML analysis in other domains, such as Weka [71] or Python's scikit-learn [72]).

Table 4. Classification of works according to the way data is collected or captured.

			#	References
Data analysis	Statistical/ mathematical analysis	Basic statistics (e.g., mean, SD)	13	[38–42,44,45,51,53,55,56,59,60]
		Variance studies (e.g., ANOVA,)	4	[39,44,51,60]
		Correlation studies (e.g., Pearson, Spearman, etc.)	5	[37,38,56,59,60]
		Other tests (e.g., *t*-Test, Tukey-Kramer, Wilcoxon test, Kruskal–Wallis test, etc.)	4	[38,53,56,60]
		Signal process (e.g., Fast Fourier Transform, Time Series Signals, "quaternions", etc.)	4	[37,42,47,57]
		Other	4	[45,49,52,61]
	Machine learning analysis	Linear regression	1	[41]
		SVM	5	[43,46,48,50,58]
		RF	3	[46,50,55]
		ANN	3	[46,50,54]
		k-NN	4	[43,46,48,50]
		Naive Bayes	2	[43,46]
	SW to perform analysis	MATLAB	4	[39,48,50,54]
		R	1	[52]
		SPSS	2	[44,51]
		N/A	17	[37,38,40–43,45–47,49,53,56–61]
NO data analysis (i.e., using data from sensor)			1	[36]

To sum up, the use of Bluetooth-based technologies prevails due to its standardization, low energy consumption, and its popularity in small devices, such as wearables. With respect to the analysis techniques applied, most of the works, besides descriptive statistics, also introduce more innovative and powerful classification techniques such as the most relevant ML algorithms such as SVM, k-NN and RF.

Finally, we believe that for greater scalability and penetration of these types of solutions, standardized autonomous data transmission mechanisms that do not require a gateway-like device, and are transparent to the end user (e.g., WiFi) should be introduced. There is also a greater added value in solutions that rely on ML techniques. Therefore, it can be foreseen both its generalization and the adoption of more sophisticated models that support the discovery of new significant patterns or indicators, incorporating new analysis techniques based on Deep Learning.

4.5. Validation of the Proposals

In relation to the validation process of the proposals analyzed in this review, criteria used included the outcomes of pilot experiments carried out in the original research; the characteristics of the sample used and the quality and nature of the tasks performed by participants; and the validity and reliability of the results obtained. To facilitate analysis, validation evidence collected from all the works surveyed, classified according to the target sport, is summarized in Table 5.

First, among the works reviewed, 4 studies discussed baseball, where pilot tests with a heterogeneous sample size were carried out, ranging from 11 users [42] to 81 [40]. Regarding the type of sports tasks addressed, the most common were warm-up exercises and fast balls. Finally, with respect to the approach followed to assess the different aspects of validity and reliability, in the four cases it was of experimental nature, more detailed in the case of [40]. This work relied on a larger sample, which allowed obtaining more representative data for validation.

In relation to the works in the field of running [41,45,56,60], all of them were based on a sample size of more than 20 users for their validation procedures, half of the participants being experienced athletes, and the other half amateur practitioners. In relation to piloted tasks, all included running tests, and additionally other types of activities as a means of comparison (e.g., walking, gym routines, swimming, cycling, or yoga). The most complete validation procedure corresponds to [41], with a sample of 35 people.

For the 4 works that did not address a specific sport, labelled as "generic" in Table 4 [37,44,58,61], the sample size used for validation varied widely, from 1 user [61] to 42 [44] or 48 [37]. The sports tasks piloted were cycling, cross training, rowing, running, squatting, stepping, walking and weight lifting. All works offer some results related to validation, regardless of the number of participants.

With respect to the 3 the works addressing basketball [48,54,55] validation was exploratory, with a small sample size and reporting little information on both the tasks carried out in the experiments, as well on the experiments themselves. In general, they are descriptive works and no formal validation is reported.

In relation to the 3 studies on cricket, the number of participants involved in validation experiments ranged between 9 [49] and 21 [39] players who had to perform several cricket movements (e.g., bowling, batting, etc.) Validation details are missing in general, except in the case of [46].

Two of the works analyzed targeted handcycling. These studies offer scarce validation details, and the sample sizes are comparatively small, ranging between 6 [36] and 12 [51] practitioners. In this case, since participants are individuals with impaired mobility, a large sample size is not so relevant for statistical significance.

Two papers about tennis were also surveyed, both of them of exploratory nature, where a basic validation process is described regardless of the sample size used (i.e., 7 [47] and 30 [50] players respectively).

Table 5. Classification of works according to the way data is collected or captured.

	Ref.	Pilot Study		Validation and Fiability [3]
		Sample	**Tasks**	
baseball	[42]	N = 11	Warm-up exercises; Baseball Throw; Volleyball Serve	-
	[40]	N = 81 (healthy pitchers)	Warm-up exercises; 10 fastballs	Yes
	[52]	N = 37	Fastballs	-
	[53]	N = 20 (young pitchers)	Pitching Motion: Fastball, Curveball, and Change-up	-
running	[41]	N = 35 (experienced runners)	Running and “other training” (e.g., gym, swimming, cycling, circuits or yoga)	Yes
	[45]	N = 20 (Best runners)	run	-
	[56]	N = 24 (health and adults)	Running treadmill and outdoor	-
	[60]	N = 30 (volunteers)	Walking and running 90′	-
generic	[61]	N = 1	Static cycling	Yes
	[37]	N = 48 (29 normal weight; 19 overweight)	Cycling, cross training, rowing, running, squatting, stepping, walking, and weight lifting	Yes
	[58]	N = 13 (healthy participants)	Human daily live’s and sports activities	Yes
	[44]	N = 42 (athletes)	High intensity training (HIT)	Yes
basketball	[48]	N = 2	-	-
	[54]	-	-	-
	[55]	N = 2	One-to-one basketball games	Yes
cricket	[49]	N = 9	5 measures/participant	-
	[39]	N = 21 (12 spin bowlers; 9 fast bowlers)	148 deliveries	-
	[46]	N = 14	Legal and un-legal bowls	Yes
hc [1]	[51]	N = 12	-	-
	[36]	N = 6 (spinal cord injury)	Handcycling	-
tenis	[47]	N = 7	400 racket blows	-
	[50]	N = 30	-	-
volleyball	[43]	N = 10 (Right-handed)	120 spiking trials	Yes
Af [2]	[59]	N = 18 (professional players)	Training, competition, and non-exercise activity thermogenesis (NEAT)	Yes
golf	[57]	Experimental	-	-
powerlifting	[38]	N = 10	Powerlifting (6 types)	Yes

[1] hc = handcycling. [2] Af = Australian football. [3] - = data not available.

Finally, of the four remaining works, three of them report validation data with a sample size around 12, addressing volleyball [43], Australian football [59], and powerlifting [38]. The last paper reviewed, aimed to improve shooting techniques in golf, was verified in the laboratory only.

To sum up, most of the works, although mostly tested with potential participants (i.e., 92.31% of the total studies reviewed), still report just exploratory data. Additional research is required to address more validation-related aspects, since they are mainly focused on studying criterion validity through the accuracy of the system. On the other hand, it is also necessary to gather additional insight on the reliability of the different proposals. In this aspect, only one work [38] addressed reliability by reporting results on intraclass correlation.

5. Conclusions

This article offers a systematic review of recent studies devoted to the innovative uses of wearable wrist devices for sports-related activities. Vendors and manufacturers of these devices do not exploit the full potential of wrist wearables for sports practice, which in turn inspired the scientific community to fill the gap left by wrist wearable manufactures by designing novel applications in this area. This situation served as the main motivation for analyzing what uses were proposed and described in the scientific literature, in order to find out the state of the art in this kind of services and applications, and also to serve as inspiration for further proposals in this promising line of work.

Research and development initiatives were reviewed that use both commercial-off-the-shelf wrist-worn wearables as well as ad hoc developed devices. This review led us to identify innovative uses in 10 specific sports, in addition to several proposals that are applicable to any sport activity. A relevant part of the proposals focuses on a more exhaustive monitoring of an individual while performing sports activities, to identify sport-specific behavioral patterns not considered by the manufacturers or for which limited support was provided by them. Other proposals were aimed at identifying specific types of movements in a given sports activity, either to improve the athlete's performance or to detect erratic or illegal behaviors. Finally, the most innovative uses encountered when compared to the features offered by device vendors are those related to the prevention of injuries. It is also worth mentioning that some of the proposals found offer as their main innovation the replacement of sophisticated monitoring equipment, often based on high-speed 3D visualization, with comparatively simple wrist wearables, which allow tracking athletes during real sports practice, rather than in the laboratory, in a cost-effective way.

The main added value of these proposals, when compared to the solutions provided by vendors themselves, usually stems from the more sophisticated data processing or from its reinterpretation. One of the most powerful tools that is being introduced to extract relevant information from data are ML techniques, which, as in other research domains, is becoming more and more popular in recent years. However, the level of validation of the proposals ranges from those that were thoroughly and rigorously tested, to those that still have to be considered as a proof of concept, as a formal validation process was not implemented.

The systematic revision completed led us to conclude that a promising line of future work would be to move from low-level (i.e., raw monitoring) and medium level (i.e., performance and behavior analysis) processes and services, to high-level and value-added services such as recommendation mechanisms. Although many solutions were identified for the effective monitoring and supervision of sports practice, tools that support the intelligent and personalized recommendation of sports routines or active injury prevention are more elusive.

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Abbreviations

The following abbreviations are used in this manuscript:

ANN	Artificial Neural Network
ANT+	Adaptive Network Topology
CCR	Correct classification rate
GNSS	Global Navigation Satellite System
GSR	Galvanic Skin Response
HR	Heart Rate
HIT	High Intensity Training
IMU	Inertial measurement unit
k-NN	k-Nearest Neighbor
MABR	Motional Analysis Ball Release
MCU	Micro Controller Unit
MIMU	Magneto inertial measurement unit
ML	Machine Learning
MSA	Monitoring of Sports Activities
NEAT	Non-Exercise Activity Thermogenesis
NFC	Near Field Communication
PCA	Principle Component Analysis
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analysis
POA	Peak Outward Acceleration
RF	Random Forest
ROC	Receiver Operating Characteristic
SVM	Support Vector Machine
VO_2 max	Maximal Oxygen Consumption

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