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Human Kinetics
BRIEF REVIEW

Unpacking the Black Box: Applications and Considerations for Using GPS Devices in Sport

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Athlete-tracking devices that include global positioning system (GPS) and microelectrical mechanical system (MEMS) components are now commonplace in sport research and practice. These devices provide large amounts of data that are used to inform decision making on athlete training and performance. However, the data obtained from these devices are often provided without clear explanation of how these metrics are obtained. At present, there is no clear consensus regarding how these data should be handled and reported in a sport context. Therefore, the aim of this review was to examine the factors that affect the data produced by these athlete-tracking devices and to provide guidelines for collecting, processing, and reporting of data. Many factors including device sampling rate, positioning and fitting of devices, satellite signal, and data-filtering methods can affect the measures obtained from GPS and MEMS devices. Therefore researchers are encouraged to report device brand/model, sampling frequency, number of satellites, horizontal dilution of precision, and software/firmware versions in any published research. In addition, details of inclusion/exclusion criteria for data obtained from these devices are also recommended. Considerations for the application of speed zones to evaluate the magnitude and distribution of different locomotor activities recorded by GPS are also presented, alongside recommendations for both industry practice and future research directions. Through a standard approach to data collection and procedure reporting, researchers and practitioners will be able to make more confident comparisons from their data, which will improve the understanding and impact these devices can have on athlete performance.

***Keywords**:* microtechnology, athlete tracking, method, MEMS, time–motion analysis

Global positioning system (GPS) is a satellite navigation network that provides location and time information of tracking devices. Initially developed for military purposes, this system now has much wider application, including its use in athlete tracking and load quantification. GPS satellites orbit the Earth and send precise time information (from an atomic clock) to the GPS receivers (at the speed of light) to determine the duration of signal transit.[1] A minimum of four satellites are required to determine the position of the GPS receiver trigonometrically. Commercial GPS systems are now commonly used in individual- and team-sports at all levels. The development and subsequent acceptance of microtechnology in sport has led to the integration of other micro inertial sensors within GPS devices, such as triaxial accelerometers, magnetometers, and gyroscopes; collectively termed as micro electrical mechanical systems (MEMS). Thus, GPS and MEMS technology provides practitioners with a wide array of data that can be used to assess athlete physical loading and activity profile.

The use of GPS in sport allows practitioners to evaluate athletic training programs, and researchers to better investigate applied research questions. Indeed, since the first paper using GPS technology in sport was produced in 2001,[2] the number of peer-reviewed research publications has increased exponentially (Figure 1). Such devices have been used mainly to investigate load monitoring in athletes[3] although other applications in assessing injury risk[4] and neuromuscular fatigue[5] have also been described. Given the wide use of GPS and MEMS derived data, it is important that both researchers and practitioners are aware of the how these data are derived. More specifically, it is important to understand how these data are generated, the factors that affect measurement validity and reliability, the impact of changes in hardware/software and how data should be reported. Therefore, the purpose of this article is to examine these issues and provide guidelines for collecting, interpreting, and reporting of GPS- and MEMS-derived data in sport.

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Reliability and Validity of Commercial GPS Devices

Athlete tracking technology is continually improving through developments in microprocessors, data processing, and software. With these advancements, researchers have conducted independent validity and reliability studies as each device/update is released from commercial suppliers. However, due to the time taken to publish such studies, GPS devices are often used in sport before essential independent information on measurement precision is available.[6] Nonetheless, it appears that both the measurement validity and reliability of GPS devices has improved with recent developments (for review see Scott et al[7]). In general, measurement precision has improved with increased sampling rate and is better in activities completed at lower speeds and with fewer changes in direction. While in the study of Johnson et al[8] 10-Hz devices were found to be superior to 15-Hz devices, the 15-Hz device used interpolated data which was not "true" GPS sampling. Thus there is a requirement to conduct further testing using true higher sampling GPS devices for further clarification. It must be noted that sampling rate alone

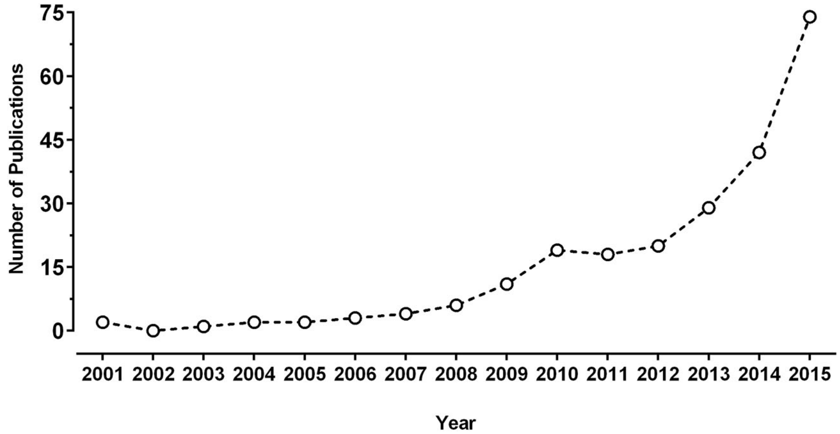

Figure 1 — The number of research studies published using commercial GPS devices from 2001 to 2015. A systematic search of all electronic databases (MEDLINE, SPORTDiscus, Web of Science, and Google Scholar) was performed from the earliest records (2001) to the last complete year (2015). The key words *GPS sport* were used for the search, and we included studies involving human subjects in applied sporting studies only.

will not improve the quality of GPS data, as factors such as the chipset processor used and position of the device on the body can also influence the output. Since this recent review[7] has described most of the validity and reliability studies, the following section will focus on the considerations for practitioners and researchers when conducting and interpreting reliability/validity research with GPS devices.

There are many manufacturers of GPS-devices, often with several models that have a variety of sampling rates, chip sets, filtering methods, and data-processing algorithms. Due to these differences in data processing between brands/models of GPS device, it is essential that the measurement validity and reliability for each is determined. Many users may not be aware these factors can influence the data obtained from these devices how GPS devices collect the data reported. For example, GPS velocity and distance can be calculated using different methods (Doppler-shift or positional differentiation). Furthermore, the accuracy of positional information to determine the distance between multiple units is different to the accuracy of a unit to measure distance alone. Accordingly, measures of velocity and distance require validation independently and in combination (eg, distance covered at certain velocities). Some studies have used latitude and longitude measures to determine the distance between devices and subsequently athletes, thus the measure of position also requires specific validation.[9,10] Therefore, it is important that researchers refer to validation studies that have used the same GPS brand/model specific to their own. It is also important that these studies report on same metrics (ie, range of speeds, distance etc.) examined in practice.

The majority of GPS validation studies have employed relatively simple field-based research designs using human subjects, with validity assessed against a known distance. However, studies that have assessed GPS-derived velocity against a criterion measure for velocity have been more complex. Some studies have used timing gates to assess velocity[11–13]; however, this approach only determines average velocity based on limited sampling points. The use of higher sampling criterion measures (ie, Laveg laser or radar gun) provide a more sensitive measure of velocity, which is important when assessing movements that involve changes in velocity such as accelerations and decelerations. These studies have investigated reliability and validity using linear running movements without any changes in direction.[12,14,15] While these studies provided a thorough assessment of velocity, acceleration, and deceleration compared with high-sampling criterion measures, the limitations were that they did not assess using sport-specific movements involving changes in direction. Other studies have employed sport-specific movement circuits,[8,11,16–19] however most of these studies are limited in the criterion measures used to evaluate velocity (eg, timing gates,[20,21]) and synchronization protocols are not well documented.

High error rates have been reported for interunit reliability across different GPS models.[11,13,16–18] This can have significant practical implications if different devices are worn by an athlete across a longitudinal period, which renders meaningful interpretation of the data difficult. It is suggested that where possible that practitioners assign a specific device to each athlete for within-athlete longitudinal monitoring.[22] It is worth noting that the extent of the interference between 2 or more devices during testing has yet to be fully explored. In the example of Buchheit et al[23] using a sled with multiple devices being used at the same time, we must first understand the influence of positioning these devices in close proximity before fully interpreting such outcomes. While interunit reliability information is available for distance it is difficult to determine for velocity. The determination of interunit reliability for velocity requires the specific velocities at which the participants move to be reproduced across trials. As human participants are unable to exactly replicate the same movement patterns (speeds and direction changes) on multiple occasions, the uses of such study designs are limited. Future research could determine interunit reliability through the use mechanical devices that allow exact velocity and distance to be replicated.

Data Collection, Processing, and Reporting Considerations

In research, detailed reporting standards are considered necessary in fields of measurement to ensure output conform to standards for reporting trials (CONSORT) or observational studies (STROBE). At present, no reporting standards exist for the use of GPS in sport, therefore, this section will highlight some considerations for collecting, processing, and reporting GPS data.

Satellite Connection and Horizontal Dilution of Precision

The signal quality received by GPS devices during data collection influences the accuracy of the data recorded. Signal quality may change depending on location and environmental obstruction (ie, stadiums), and should be recorded to ensure that longitudinal analysis can be carried out with confidence.[24] To evaluate the fidelity of the data collected, signal quality can be judged based on the number of satellites interacting with the receiver together with their orientation in the atmosphere.[25] It is equally important that the satellites connected have adequate signal strength to the specific device. While GPS devices require a minimum of 4 satellites for adequate connection, the higher the number of connected satellites would increase the coverage of the device. Anecdotally, devices connected to less than 6 satellites would tend to have a weaker connection and thus data quality. The recent development of multiple Global Navigation Satellite Systems (GNSS) has improved both the availability and signal strength of surrounding satellites. However, there has yet to be a direct comparison study completed comparing the data quality of GPS versus GNSS in a sporting context, which lends to future research. In addition, research is also required to identify whether the inclusion of GNSS technology improves data quality in different stadium environments, which has often been a limitation of GPS-based systems.

The horizontal dilution of precision (HDOP) provides a measure of the accuracy of the GPS horizontal positional signal determined by the geometrical organization of the satellites. When satellites are bunched together HDOP is high and precision is poor whereas when satellites are spread out HDOP is low and precision is good. Values range from 0 to 50,[25] with a value less than 1 considered ideal. While some researchers have detailed the average number of satellites and/or HDOP connected to the devices used during data collection,[13,14,16,18,22,23,26] many have not provided these details that make study conclusions difficult. While all GPS devices are able to collect information on the number of satellites and HDOP, not all manufacturers allow this data to be accessed by the user. Therefore, we recommend that manufacturers make this information available to practitioners and researchers.

In a practical setting, practitioners may be providing training and competition reports to coaches based on erroneous data. This can have significant implications for the coaching process, as changes may be made to the athletes program based on poor quality data. Therefore, we strongly recommend that practitioners ensure they have confidence in the data they use on a daily basis to make practice-changing decisions. We recommend that users check the data quality using the before mentioned satellite and HDOP information and exclude any data files that fall outside acceptable ranges for a considerable portion of the file. It should also be noted that there is no clear "gold standard" guidelines to allow users to clearly objectively identify files of poor data quality. Further work is required in this area to improve the reporting standards guidelines for practitioners.

Data-Exclusion Criteria

Due to factors outside of the practitioner's control, there may be instances in which data collected should be excluded from any subsequent analysis. Indeed, the number of satellites connected and HDOP are methods that can be used to determine whether to exclude data. Moreover, raw traces of velocity and acceleration should also be inspected for irregularities generated from the device itself (ie, spikes in the data). These irregularities may occur due to sudden loss in satellite signal connection leading to a delayed detection of locomotion. A combination of these processes is encouraged to inform judgments regarding data exclusion, and researchers are encouraged to detail the specific criteria adopted and the proportion of discarded data (ie, Weston et al[26]).

Velocity and Acceleration Data

The GPS devices can calculate distance and velocity via two different methods, from positional differentiation or Doppler shift. The GPS devices calculate position (latitude and longitude) using information of the distance of each satellite to the device and then triangulating the devices location. Subsequently distance is calculated via positional differentiation (change in location with each signal), from which velocity can be derived (distance over time). Velocity can also be calculated by measuring the change in frequency of the satellite emitted periodic signal (Doppler shift). This provides an almost instantaneous measure of velocity from which distance can be derived (velocity multiplied by time). Velocity calculated via Doppler-shift has shown a higher level of precision and less error compared with velocity calculated via positional differentiation during linear running at a range of velocities for 1-Hz GPS devices.[27] Whether such differences exist in units sampling at higher frequencies is unclear, as is the comparison of distance calculated via each method. Therefore further validation of commercial systems is required. Current commercial systems (Catapult Sports, GPSports) determine distance via positional differentiation and velocity via Doppler shift (personal communication with manufacturers). Manufacturers should include this information in documentation pertaining to their devices as it is relevant for both practitioners and researchers. If velocity and distance are calculated from 2 different methods it is an important consideration as validation is required of both measures.

Acceleration that is measured using the GPS is often derived from Doppler-shift velocity. The time interval over which acceleration is calculated can significantly alter the data with a wider interval resulting in a smoothing effect on the data. Typically, acceleration is calculated over 0.2 or 0.3 second when using 10-Hz GPS, although the most appropriate interval will depend on the brand and model of the device. After acceleration is calculated the data may be smoothed using different filtering techniques, often chosen at the discretion of the manufacturer. Filters that have been used by current manufacturers include moving average, median, and exponential filters. Velocity data may also be smoothed using the aforementioned filters. Often these filters are predetermined by the manufacturers software, however if the raw data can be exported the users can apply their own custom filters.

Practitioners should be aware that any changes to the way their data are filtered is likely to have implications on their choice of thresholds (velocity/acceleration) and the selection of a minimum time in which efforts (velocity/acceleration) are detected. In most manufacturers' software, velocity metrics are calculated from Doppler estimates; nonetheless clarification of the method of determination would facilitate the interpretation of GPS data by research consumers. In addition, it is a common misconception that the accelerometers within these devices are involved in the calculation of GPS acceleration, however this is not the case, and accelerometer-derived acceleration/deceleration are distinctly separate metrics.

Raw Data Versus Software-Derived Data

Manufacturer software often includes algorithms to identify poor quality data, and automatically interpolate, smooth or extract data (ie, software-derived data). This is helpful in the practical setting where fast evaluation of training/competition loads is necessary to assess performance and inform exercise prescription. However, greater clarity of the filters and algorithms used to process the data are required from manufacturers in order for users to understand the metrics produced. Indeed, users should be aware that data processing by commercial software would be subject to change due to changes in technology and processing algorithms.[23] In circumstances where researchers are conducting studies using historical or longitudinal data, it is recommended to export and analyze the data using the same software version and disclose this information to research consumers.

Some practitioners and researchers prefer to export raw data from commercial software and process it independently.[26,28–30] This allows data to be analyzed in greater detail such as the use of rolling periods[31] or for custom algorithms to identify new metrics. Custom processing of raw data also allows the user to provide details on error detection, data filtering and reporting processes to facilitate appropriate interpretation and replication by others. However, manufacturer proprietary software often uses data-processing algorithms that are subject to intellectual property protection, and their details are not disclosed to users. The lack of transparency about these processing algorithms can make external validation of these metrics difficult.

The "raw" data exported from many commercial software are often prefiltered by the receivers' firmware to reduce the noise within the GPS signal. Firmware refers to a writable control store within the devices chipsets that contains microcode defined by the manufacturer's instruction set. The type of processing is dependent upon the model and version of the firmware, therefore each firmware version that processes the data differently will require validation. Due to the potential influence of firmware updates on data, manufacturers are encouraged to inform users on the influence of these updates and researchers should report the firmware version used during data collection.

Minimum Effort Duration

A data processing feature that is customizable by some manufacturer software is the criteria used to identify movement efforts such as sprints or accelerations. Users select the minimum time to delineate the minimum effort duration above a particular speed or acceleration threshold required for an effort to be recorded. For example, the detection of a sprint effort defined at >7 m/s with a minimum time of 0.4 second, requires speed to be maintained >7 m/s for a minimum of 4 consecutive samples when sampling at 10 Hz. This approach ensures that unrealistic calculation of efforts, such as those that arise from GPS random error or spikes in speed, are not included (eg, efforts lasting <0.1 s are counted as sprint efforts).

The identification of the end point of an effort is also important as speed may oscillate around a set threshold, therefore a minimum time in which speed is required to fall below a threshold should also be determined. For example, an athlete's speed may oscillate around the sprint threshold of 7 m/s. If a short minimum time is used to detect the end of an effort (eg, 0.1 s) than if the athlete's speed fell below the threshold for one sample, they would be reported to have performed 2 or more sprints efforts when only one effort was likely to occur. Currently there is no consensus on an optimal duration that should be set to identify discrete efforts; however, too short duration can result in a high number of efforts being reported. Moreover, the minimum duration used to identify the start and end of an effort can have a greater effect on identifying short duration efforts such as accelerations and decelerations. A conservative approach for users would be to set a longer duration above a threshold as the criteria for accelerations and decelerations. Practitioners should be aware that this user-defined criterion may have a marked effect on their results and should be consistent with their choice of minimum time. In addition, differences between studies in the criteria used to define efforts or where the criteria are not defined make it difficult to compare findings. Further complicating this issue is that practitioners may use a variety of sprint effort definitions. While some practitioners will only consider movement above a specific threshold, others may wish to include the preceding acceleration. Accordingly, we recommend that details regarding minimum effort duration should be reported in research. Future research should also look to link the effort duration analysis with clear physiological rationale such as what clearly defines an anaerobic- and aerobic-type single effort through the GPS data.

GPS and MEMS Device Preparation and Considerations

When using GPS/MEMS devices, it is important to ensure that the correct procedures for data collection are followed and reported. For example, devices should be calibrated by the manufacturer before data collection and the details provided to the user. Further, athletes should wear the devices in appropriate tight-fitting garments to hold the device and minimize unwanted movement. Poor fitting of devices may negatively affect accelerometer data. Users should also ensure that devices have satellite connection before any data collection (known as GPS lock). This can be achieved by placing the devices in a clear outdoor space and allowing sufficient time to achieve GPS lock (usually indicated on the manufacturer's device by flashing light signals).

Real-Time Testing

It is common for sport scientists embedded in sport to use the real-time data features of the manufacturer's software to provide feedback and inform decisions in training and competition. Coaches and players may seek feedback on loads (during training to see if they have achieved predetermined targets. However, the quality of real-time data can be influenced by a number of factors including the distance of the antennae from the GPS device and the processing ability of the GPS device to stream data. Indeed, an earlier study comparing differences between real-time data and "postdownload" data showed a discrepancy in the output suggesting caution should be taken when interpreting real-time data.[32] However, since this research was completed, GPS and real-time technology has improved. Therefore, we recommended that further research be conducted to establish the accuracy of real-time data, and that for quality assurance purposes that GPS data be downloaded post activity for reporting.

Speed Thresholds

The total distance covered during a training session or competitive event is considered a global index of the athletes' workload and it is often a stable metric.[33] However, GPS data are often categorized into speed zones in an attempt to understand the "locomotor profile" or "intensity distribution" of the athletes' external loading. The following section will examine issues relating to determining speed zone thresholds for GPS data for team-sport athletes, with specific discussion on justification for selecting absolute and relative speed zones, and methodological approaches and practical considerations for individualizing speed zones.

The customizability of speed thresholds afforded by GPS software resulted in a range in the number of zones and their thresholds used to demarcate different locomotor activities (see: Cummins et al[3] and Aughey[34] for more detail). Indeed, while several previous authors have suggested standardization of speed-zone thresholds to permit between sport or competition contrasts,[3,34,35] differences in the technology available,[36,37] equipment manufacturers,[8,17] sampling frequencies,[8,16,36,38] software versions,[23] and data-processing techniques make it difficult to draw confident inferences about appropriate speed thresholds from previous studies. While between-study comparisons may be permitted with relative GPS metrics (ie, % of total distance covered[39]), the specific nature and demands of each sport and its athlete cohort, together with the range of contextual factors that influence external loading patterns[40–43] may render threshold standardization academic, and of little relevance for industry practice.

A specific practical issue for users working with athletes is determining appropriate speed thresholds. Ultimately, selection of absolute (or arbitrary) speed thresholds to examine the locomotor profile of an activity bout is at the discretion of the user/researcher and informed by the particular population being assessed. Yet, an appropriate theoretical framework to inform threshold selection has been historically absent in the research literature, and seemingly based on early locomotor category based time–motion analyses, which were subjective in nature. For example, in the research that has examined youth and female populations there has been little justification provided for the speed zones selected, except that the thresholds were lowered to reflect the lower locomotor performance capacities of younger[44] and female cohorts.[45] One approach to has been to use mean cohort-specific physical fitness (ie, anaerobic threshold[46,47]) or performance characteristics such as maximal sprint speed[48,49] from normative data sets to anchor player-independent (arbitrary) speed thresholds. The advantage of this approach is that the locomotor profile of the activity will be representative for the cohort, however, this will be limited by frequent changes in speed zones owing to squad composition and seasonal variations in physical fitness, precluding longitudinal analysis of locomotor trends. Yet, longitudinal tracking of external load is relevant for young athletes for the purposes of session evaluation and prescription, and may also be used for educational, comparative, and selection purposes in industry practice. Accordingly, selection of universal arbitrary thresholds to demarcate zones of equal bandwidth may be recommended for each athlete/squad in an organization (ie, 0–5, 5–10, 10–15, 15–20, >25 km/h), for which the qualitative locomotor descriptor used for each zone (ie, moderate-, high-, very-high-speed running, sprint) could be repositioned with age or biological maturation status to better reflect the physical capabilities of the athlete/squad. We recommend that users reflect upon the cohort being monitored and the value of examining the locomotor profile of external loading to inform their prescription of absolute speed thresholds.

To complement GPS data categorized by absolute or cohort-specific speed zones (player-independent), users may also consider individualizing the thresholds for each athlete according to their fitness attributes. The integration of athletes' fitness characteristics into external load metrics may provide a proxy to determine the dose response in competition settings in which measures of internal training load (or the response to the stimulus) are not always feasible. This technique discerns the individuals' specific locomotor profile (or "intensity distribution") and may inform the evaluation of external load and the ensuing prescription.[50–52] For example, comparing the high-speed distance covered above an arbitrary (player-independent) threshold between two English Premier League players, who fulfilled similar tactical roles in the same competitive matches, resulted in trivial differences (~5%); yet application of individualized zones (≥velocity corresponding to the respiratory compensation threshold) yielded a 41% difference in the "high-intensity" running performed between the players.[50] More recently, Hunter et al[52] presented the case of a player whose fitness (running speeds corresponding to the respiratory compensation threshold and maximal oxygen consumption) decreased within a season, which corresponded with increased intensity of match play (ie, greater high-speed running and sprinting). Such cases were only identifiable with the application of individualized speed thresholds, highlighting the advantages of developing player-specific individual speed thresholds. Indeed, when both arbitrary and individualized speed thresholds are used in conjunction, greater insights into the player loading of individuals and teams of athletes may be achieved than with either method alone. However, while the ability to customize individual players speed thresholds is already available in some GPS commercial software applications, it is a laborious process, which may partly explain why this approach is not a commonly adopted in industry practice.[53] Nonetheless, future commercial GPS software developments/upgrades might include the capacity to dual process and compare data according to both absolute and relative speed zones, which will assist practitioners to implement this approach in a time-efficient manner.

Practitioners have a range of options available in the determination and application of individualized speed thresholds. Previous research has used measures of anaerobic threshold,[47,50,51] intermittent-exercise capacity,[54] maximal aerobic speed,[52,55,56] peak running speed,[44,57–59] or a combination of two[55,56] or three[52] of these measures to determine individualized speed thresholds. Users are cautioned against using one of these capacities in isolation to individualize the complete locomotor profile, because data can be skewed dependent upon the phenotype of the athlete, which may result in erroneous interpretation (see examples presented in Hunter et al[52]). For instance, using fractions of peak sprint speed to demarcate high-speed running has become common in the research literature,[57–59] yet this approach has no physiological rationale. A limitation of this approach is that it assumes that faster players also have a higher transition speeds into the high or supra-maximal intensity domains, which may not always be the case.

Although most of the previous research to date on individualized speed thresholds has adopted resource-intensive laboratory procedures to determine the fitness characteristics of athletes (ie, maximal aerobic capacity, anaerobic threshold, etc), these attributes can be determined in field settings using an appropriate test battery in conjunction with suitable monitoring technology (ie, VAM-EVAL and peak speed assessment[56,60]). The application of physiological thresholds determined from continuous exercise tests (such as the VAM-EVAL) to demarcate speed zones for intermittent activities such as team sport has been questioned,[26,61] and the use of functionally relevant tests (ie, Yo-Yo tests) has been recommended.[61] However, since most of the popular team-sport fitness tests (ie, Yo-Yo, multistage fitness test) require a combination of endurance, change of direction, and acceleration capabilities,[62,63] they may be more suited for evaluating changes in game readiness or "fitness," rather than determining transitions in exercise intensity. Moreover, the nature of these fitness tests also precludes the determination of relevant[47,50–52] submaximal physiological thresholds. Indeed, the velocity corresponding to anaerobic threshold is quite sensitive to changes in team-sport training status owing to a development phase (ie, preseason)[64] or an injury-induced training interruption,[52] and therefore may have value in determining individual speed zone thresholds. However, since a consensus is absent, users should consider which fitness tests are most appropriate to determine individualized speed thresholds before application. Moreover, the frequency in which fitness tests can be administered around the competition schedule should also be contemplated, so that individualized speed zones reflect changes in fitness capabilities during the in-season period.[52]

The use of speed zones, whether arbitrary, individualized, or in combination, masks the intermittent nature of many sports, and underestimates metabolically taxing activities such as abrupt changes in speed,[65] direction,[66] or the mode of locomotion.[67] For instance, an athletes who performs predominantly in confined spaces, rarely has the opportunity to reach the criterion speeds for high-speed running or sprint zones, yet the energy cost of their maximal accelerations may be 3-fold that of an athlete running at constant speeds.[65] Hence, while individualizing speed thresholds based on physiological classifications of intensity domains or performance attributes may offer additional insight into the athlete's work rate, it cannot be considered a criterion measure of the intensity distribution in highly intermittent sports.

The complexities and challenges surrounding the application of individualized speed thresholds, such as lack of consensus in selecting and assessing appropriate fitness attributes, and difficulties in executing regular fitness tests with large squads of athletes, present significant barriers to its implementation in practice. This is further compounded by the dearth of evidence regarding its efficacy, and its inability to quantify metabolically demanding activities at low movement speeds. Intuitively, evaluating the athletes' external load relative to their performance/fitness capacities is a logical practice, but further work is warranted to examine the utility of individualized versus arbitrary speed zones to predict injury risk resulting from mismanagement or poor control of load prescription.[68,69] Research is also necessary to determine the dose response of external load evaluated via individualized vs. arbitrary speed zones, to changes in fitness. Such information will assist the user to make informed decisions about the evaluation of GPS data, and how this informs training prescription.

Inertial Sensors

The majority of research using GPS devices in sport has focused on the quantification of external load using metrics such as total and high speed running distances covered.[3] Fewer studies have examined the loading recorded through the inertial measurement units (IMUs) available in MEMS devices. These sensors typically sample at a higher frequency (typically 100 Hz) compared with the GPS (5–20 Hz). The IMUs have the advantage that they can be used indoors as they do not require a satellite connection.

The accelerometer-derived load measures can vary between different manufacturers, with the most common being PlayerLoad™ (Catapult Sports) and Body Load (GPSports). These measures are based on the instantaneous rate of change in acceleration in each of the 3 vectors (*x*-, *y*-, and *z*-axis) as a proxy for mechanical load. Both measures of accelerometer load have demonstrated acceptable levels of interunit and intraunit reliability.[70,71] However, caution has been recommended when measuring the absolute magnitude of acceleration when comparing to a criterion-referenced accelerometer.[71] It should also be noted that as with GPS-based measures, the IMU outputs can be influenced by the type of filtering procedures that the manufacturer adopts.

The vector magnitude accelerometer data are sensitive to within-athlete changes in both internal and external measures of exercise intensity[5,72] and has been shown to detect changes in movement strategy that may be indicative of acute[18,73,74] and chronic fatigue.[75,76] Studies have suggested that changes in the accelerometer may reflect changes in lower-limb stiffness,[71,73–75] but users should be aware that upper-body kinematics influence the distribution of load accumulated in each movement vector (plane) when devices are harnessed at the upper trunk.[72,73] Inferences regarding the distribution of loading in different vectors are also constrained in some devices, as changes in the orientation of the unit are not considered by the accelerometer (eg, a rugby tackle). Therefore, MEMS users working in sports that are characterized by wrestling, tackling, and impacts may be unable to detect changes in movement strategy during games, and further work is necessary to refine accelerometer metrics. Practitioners are also cautioned regarding the large between-athletes variability in loading patterns observed,[72–74] which impedes comparisons between different players. The different loading patterns between athletes may be caused by differences in running economy, stride characteristics, and movement artifact of the device dependent upon its fitting within the athlete's garment. Further work is necessary in this area to examine the determinants of accelerometer data in sporting contexts.

The use of IMUs in sport has also led to the development of algorithms designed to detect sport-specific actions or movement (for review see Chambers et al[77]). Such technology has been used to detect collisions in rugby league[78,79] fast bowling in cricket,[80] swimming,[81] and cross-country skiing[82] movements. While these studies have used single devices worn on the upper back, other studies have used multiple devices to identify these sport-specific actions.[83–86] A practical consideration when using MEMS data are to ensure that devices are fitted securely in the same position for all sessions. This is of particular importance when using match jerseys with custom made pouches sown into the back which may differ with training jerseys, and users should ensure that athletes wear the same housing garment in routine training/competition. While the use of multiple sensors may provide the means to create sensitive algorithms to detect sport-specific actions, it is important that these sensors can be worn practically by athletes during normal practices. It may be the case that the current available sampling rates (ie, 100 Hz) are not sensitive enough for the development of new algorithms and manufacturers may look to provide higher sampling data.

Summary and Recommendations

The present article has discussed some of the issues and considerations that researchers and practitioners should be aware of when using GPS and MEMS devices. Currently there is no clear consensus on the appropriate reporting standards using such devices. Therefore, we have detailed some key recommendations below to prompt an improvement in reporting standards both in research and also applicable in applied practice.

- Researchers should include information regarding the number of satellites, HDOP, device brand/model, sampling frequency and software/firmware versions in any published research, together with details of data inclusion/exclusion criteria.

- Researchers and practitioners should be aware of the minimum time used to identify efforts and the smoothing filters used to derive acceleration data. Further, this information should be included in any published research.
- Manufacturers should provide information regarding any changes relating to data processing with updates to software or firmware.
- Practitioners are urged to carefully consider the justification for the short- and long-term application of arbitrary and/or individualized speed thresholds to examine the locomotor (or intensity) distribution of external load.
- Users are cautioned against using one physiological and/or performance metric to anchor multiple individualized speed zones and to reflect on practical considerations such as routine fitness testing, test-battery selection, and time-efficient processing of individualized GPS data.
- Comparing accelerometer data between different athletes to make judgments regarding external load should be undertaken with caution due to the large degree of variation.
- Inertial sensors and the use of sport-specific algorithms provide an insight into the future of load monitoring, although this is a relatively new area that requires further work to ensure reliable and valid data are produced, and to refine existing metrics.

References

1. Larsson P. Global positioning system and sport-specific testing. *Sports Med*. 2003;33(15):1093–1101. PubMed doi:10.2165/00007256-200333150-00002
2. Larsson P, Henriksson-Larsen K. The use of dGPS and simultaneous metabolic measurements during orienteering. *Med Sci Sports Exerc*. 2001;33(11):1919–1924. PubMed doi:10.1097/00005768-200111000-00018
3. Cummins C, Orr R, O'Connor H, West C. Global positioning systems (GPS) and microtechnology sensors in team sports: a systematic review. *Sports Med*. 2013;43(10):1025–1042. PubMed doi:10.1007/s40279-013-0069-2
4. Gabbett TJ, Ullah S. Relationship between running loads and soft-tissue injury in elite team sport athletes. *J Strength Cond Res*. 2012;26(4):953–960. PubMed doi:10.1519/JSC.0b013e3182302023
5. Buchheit M, Gray A, Morin JB. Assessing stride variables and vertical stiffness with GPS-embedded accelerometers: preliminary insights for the monitoring of neuromuscular fatigue on the field. *J Sports Sci Med*. 2015;14(4):698–701. PubMed
6. Russell M, Sparkes W, Northeast J, et al. Changes in acceleration and deceleration capacity throughout professional soccer match-play. *J Strength Cond Res*. 2016;30(10):2839–2844. PubMed
7. Scott MT, Scott TJ, Kelly VG. The validity and reliability of global positioning systems in team sport: a brief review. *J Strength Cond Res*. 2016;30(5):1470–1490. PubMed
8. Johnston RJ, Watsford ML, Kelly SJ, Pine MJ, Spurrs RW. Validity and interunit reliability of 10 Hz and 15 Hz GPS units for assessing athlete movement demands. *J Strength Cond Res*. 2014;28(6):1649–1655. PubMed doi:10.1519/JSC.0000000000000323
9. Aguiar M, Goncalves B, Botelho G, Lemmink K, Sampaio J. Footballers' movement behaviour during 2-, 3-, 4- and 5-a-side small-sided games. *J Sports Sci*. 2015;33(12):1259–1266. PubMed doi:10.1080/02640414.2015.1022571
10. Gonçalves BV, Figueira BE, Macas V, Sampaio J. Effect of player position on movement behaviour, physical and physiological performances during an 11-a-side football game. *J Sports Sci*. 2014;32(2):191–199. PubMed doi:10.1080/02640414.2013.816761
11. Coutts AJ, Duffield R. Validity and reliability of GPS units for measuring movement demands of team sports. *J Sci Med Sport*. 2010;13(1):133–135. PubMed doi:10.1016/j.jsams.2008.09.015
12. Castellano J, Casamichana D, Calleja-González J, San Román J, Ostojic SM. Reliability and accuracy of 10 Hz GPS devices for short-distance exercise. *J Sports Sci Med*. 2011;10(1):233–234. PubMed
13. Waldron M, Worsfold P, Twist C, Lamb K. Concurrent validity and test-retest reliability of a global positioning system (GPS) and timing gates to assess sprint performance variables. *J Sports Sci*. 2011;29(15):1613–1619. PubMed doi:10.1080/02640414.2011.608703
14. Varley MC, Fairweather IH, Aughey RJ. Validity and reliability of GPS for measuring instantaneous velocity during acceleration, deceleration, and constant motion. *J Sports Sci*. 2012;30(2):121–127. PubMed doi:10.1080/02640414.2011.627941
15. Nagahara R, Botter A, Rejc E, et al. Concurrent validity of GPS for deriving mechanical properties of sprint acceleration. *Int J Sports Physiol Perform.* 2017;12(1):129–132. http://dx.doi.org/10.1123/ijspp.2015-0566
16. Jennings D, Cormack S, Coutts AJ, Boyd L, Aughey RJ. The validity and reliability of GPS units for measuring distance in team sport specific running patterns. *Int J Sports Physiol Perform*. 2010;5(3):328–341. PubMed doi:10.1123/ijspp.5.3.328
17. Petersen C, Pyne D, Portus M, Dawson B. Validity and reliability of GPS units to monitor cricket-specific movement patterns. *Int J Sports Physiol Perform*. 2009;4(3):381–393. PubMed doi:10.1123/ijspp.4.3.381
18. Portas MD, Harley JA, Barnes CA, Rush CJ. The validity and reliability of 1-Hz and 5-Hz global positioning systems for linear, multidirectional, and soccer-specific activities. *Int J Sports Physiol Perform*. 2010;5(4):448–458. PubMed doi:10.1123/ijspp.5.4.448
19. Vickery WM, Dascombe BJ, Baker JD, Higham DG, Spratford WA, Duffield R. Accuracy and reliability of GPS devices for measurement of sports-specific movement patterns related to cricket, tennis, and field-based team sports. *J Strength Cond Res*. 2014;28(6):1697–1705. PubMed doi:10.1519/JSC.0000000000000285
20. Stanley J, Peake JM, Buchheit M. Consecutive days of cold water immersion: effects on cycling performance and heart rate variability. *Eur J Appl Physiol*. 2013;113(2):371–384. PubMed doi:10.1007/s00421-012-2445-2
21. Gray AJ, Jenkins D, Andrews MH, Taaffe DR, Glover ML. Validity and reliability of GPS for measuring distance travelled in field-based team sports. *J Sports Sci*. 2010;28(12):1319–1325. PubMed doi:10.1080/02640414.2010.504783
22. Jennings D, Cormack S, Coutts AJ, Boyd L, Aughey RJ. Variability of GPS units for measuring distance in team sport movements. *Int J Sports Physiol Perform*. 2010;5(4):565–569. PubMed doi:10.1123/ijspp.5.4.565
23. Buchheit M, Al Haddad H, Simpson BM, et al. Monitoring accelerations with GPS in football: time to slow down? *Int J Sports Physiol Perform*. 2014;9(3):442–445. PubMed doi:10.1123/ijspp.2013-0187
24. Williams M, Morgan S. Horizontal positioning error derived from stationary GPS units: a function of time and proximity to building infrastructure. *Int J Perform Anal Sport*. 2009;9(2):275–280.
25. Witte TH, Wilson AM. Accuracy of non-differential GPS for the determination of speed over ground. *J Biomech*. 2004;37(12):1891–1898. PubMed doi:10.1016/j.jbiomech.2004.02.031
26. Weston M, Siegler J, Bahnert A, McBrien J, Lovell R. The application of differential ratings of perceived exertion to Australian Football

League matches. *J Sci Med Sport*. 2015;18(6):704–708. PubMed doi:10.1016/j.jsams.2014.09.001
27. Townshend AD, Worringham CJ, Stewart IB. Assessment of speed and position during human locomotion using nondifferential GPS. *Med Sci Sports Exerc*. 2008;40(1):124–132. PubMed doi:10.1249/mss.0b013e3181590bc2
28. Kempton T, Sirotic AC, Coutts AJ. Between match variation in professional rugby league competition. *J Sci Med Sport*. 2014;17(4):404–407. PubMed doi:10.1016/j.jsams.2013.05.006
29. Kempton T, Sullivan C, Bilsborough JC, Cordy J, Coutts AJ. Match-to-match variation in physical activity and technical skill measures in professional Australian football. *J Sci Med Sport*. 2015;18(1):109–113. PubMed doi:10.1016/j.jsams.2013.12.006
30. Coutts AJ, Quinn J, Hocking J, Castagna C, Rampinini E. Match running performance in elite Australian rules football. *J Sci Med Sport*. 2010;13(5):543–548. PubMed doi:10.1016/j.jsams.2009.09.004
31. Varley MC, Elias GP, Aughey RJ. Current match-analysis techniques' underestimation of intense periods of high-velocity running. *Int J Sports Physiol Perform*. 2012;7(2):183–185. PubMed doi:10.1123/ijspp.7.2.183
32. Aughey RJ, Falloon C. Real-time versus post-game GPS data in team sports. *J Sci Med Sport*. 2010;13(3):348–349. PubMed doi:10.1016/j.jsams.2009.01.006
33. Rampinini E, Bosio A, Ferraresi I, Petruolo A, Morelli A, Sassi A. Match-related fatigue in soccer players. *Med Sci Sports Exerc*. 2011;43(11):2161–2170. PubMed doi:10.1249/MSS.0b013e31821e9c5c
34. Aughey RJ. Applications of GPS technologies to field sports. *Int J Sports Physiol Perform*. 2011;6(3):295–310. PubMed doi:10.1123/ijspp.6.3.295
35. Dwyer DB, Gabbett TJ. Global positioning system data analysis: velocity ranges and a new definition of sprinting for field sport athletes. *J Strength Cond Res*. 2012;26(3):818–824. PubMed doi:10.1519/JSC.0b013e3182276555
36. Randers MB, Mujika I, Hewitt A, et al. Application of four different football match analysis systems: a comparative study. *J Sports Sci*. 2010;28(2):171–182. PubMed doi:10.1080/02640410903428525
37. Buchheit M, Allen A, Poon TK, Modonutti M, Gregson W, Di Salvo V. Integrating different tracking systems in football: multiple camera semi-automatic system, local position measurement and GPS technologies. *J Sports Sci*. 2014;32(20):1844–1857. PubMed doi:10.1080/02640414.2014.942687
38. Akenhead R, French D, Thompson KG, Hayes PR. The acceleration dependent validity and reliability of 10 Hz GPS. *J Sci Med Sport*. 2014;17(5):562–566. PubMed doi:10.1016/j.jsams.2013.08.005
39. Carling C. Interpreting physical performance in professional soccer match-play: should we be more pragmatic in our approach? *Sports Med*. 2013;43(8):655–663. PubMed doi:10.1007/s40279-013-0055-8
40. Sullivan C, Bilsborough JC, Cianciosi M, Hocking J, Cordy J, Coutts AJ. Match score affects activity profile and skill performance in professional Australian football players. *J Sci Med Sport*. 2014;17:326–331. PubMed doi:10.1016/j.jsams.2013.05.001
41. Sullivan C, Bilsborough JC, Cianciosi M, Hocking J, Cordy JT, Coutts AJ. Factors affecting match performance in professional Australian football. *Int J Sports Physiol Perform*. 2014;9(3):561–566. PubMed doi:10.1123/ijspp.2013-0183
42. Mendez-Villanueva A, Buchheit M. Football-specific fitness testing: adding value or confirming the evidence? *J Sports Sci*. 2013;31(13):1503–1508. PubMed doi:10.1080/02640414.2013.823231
43. Lago C. The influence of match location, quality of opposition, and match status on possession strategies in professional association football. *J Sports Sci*. 2009;27(13):1463–1469. PubMed doi:10.1080/02640410903131681
44. Buchheit M, Mendez-Villanueva A, Simpson BM, Bourdon PC. Match running performance and fitness in youth soccer. *Int J Sports Med*. 2010;31(11):818–825. PubMed doi:10.1055/s-0030-1262838
45. Mujika I, Santisteban J, Impellizzeri FM, Castagna C. Fitness determinants of success in men's and women's football. *J Sports Sci*. 2009;27(2):107–114. PubMed doi:10.1080/02640410802428071
46. Vigne G, Gaudino C, Rogowski I, Alloatti G, Hautier C. Activity profile in elite Italian soccer team. *Int J Sports Med*. 2010;31(5):304–310. PubMed doi:10.1055/s-0030-1248320
47. Clarke AC, Anson J, Pyne D. Physiologically based GPS speed zones for evaluating running demands in women's rugby sevens. *J Sports Sci*. 2015;33(11):1101–1108. PubMed doi:10.1080/02640414.2014.988740
48. Harley JA, Barnes CA, Portas M, et al. Motion analysis of match-play in elite U12 to U16 age-group soccer players. *J Sports Sci*. 2010;28(13):1391–1397. PubMed doi:10.1080/02640414.2010.510142
49. Saward C, Morris JG, Nevill ME, Nevill AM, Sunderland C. Longitudinal development of match-running performance in elite male youth soccer players. *Scand J Med Sci Sports*. 2016;26(8):933–942. PubMed
50. Lovell R, Abt G. Individualization of time–motion analysis: a case-cohort example. *Int J Sports Physiol Perform*. 2013;8(4):456–458. PubMed doi:10.1123/ijspp.8.4.456
51. Abt G, Lovell R. The use of individualized speed and intensity thresholds for determining the distance run at high-intensity in professional soccer. *J Sports Sci*. 2009;27(9):893–898. PubMed doi:10.1080/02640410902998239
52. Hunter F, Bray J, Towlson C, et al. Individualisation of time-motion analysis: a method comparison and case report series. *Int J Sports Med*. 2015;36(1):41–48. PubMed
53. Akenhead R, Nassis GP. Training load and player monitoring in high-level football: current practice and perceptions. *Int J Sports Physiol Perform.* 2016;11(5):587–593. http://dx.doi.org/10.1123/ijspp.2015-0331
54. Buchheit M, Hammond K, Bourdon PC, et al. Relative match intensities at high altitude in highly-trained young soccer players (ISA3600). *J Sports Sci Med*. 2015;14(1):98–102. PubMed
55. Lacome M, Piscione J, Hager JP, Bourdin M. A new approach to quantifying physical demand in rugby union. *J Sports Sci*. 2014;32(3):290–300. PubMed doi:10.1080/02640414.2013.823225
56. Mendez-Villanueva A, Buchheit M, Simpson B, Bourdon PC. Match play intensity distribution in youth soccer. *Int J Sports Med*. 2013;34(2):101–110. PubMed
57. Cahill N, Lamb K, Worsfold P, Headey R, Murray S. The movement characteristics of English Premiership rugby union players. *J Sports Sci*. 2013;31(3):229–237. PubMed doi:10.1080/02640414.2012.727456
58. Gabbett TJ. Use of relative speed zones increases the high-speed running performed in team sport match play. *J Strength Cond Res*. 2015;29(12):3353–3359. PubMed doi:10.1519/JSC.0000000000001016
59. Reardon C, Tobin DP, Delahunt E. Application of individualized speed thresholds to interpret position specific running demands in elite professional rugby union: a GPS study. *PLoS One*. 2015;10(7):e0133410. PubMed doi:10.1371/journal.pone.0133410
60. Buchheit M, Solano R, Millet GP. Heart-rate deflection point and the second heart-rate variability threshold during running exercise in trained boys. *Pediatr Exerc Sci*. 2007;19(2):192–204. PubMed doi:10.1123/pes.19.2.192

61. Bradley PS, Vescovi JD. Velocity thresholds for women's soccer matches: sex specificity dictates high-speed running and sprinting thresholds—Female Athletes in Motion (FAiM). *Int J Sports Physiol Perform*. 2015;10(1):112–116. PubMed doi:10.1123/ijspp.2014-0212
62. Castagna C, Impellizzeri FM, Chamari K, Carlomagno D, Rampinini E. Aerobic fitness and Yo-Yo continuous and intermittent tests performances in soccer players: a correlation study. *J Strength Cond Res*. 2006;20(2):320–325. PubMed
63. Castagna C, Impellizzeri F, Cecchini E, Rampinini E, Alvarez JC. Effects of intermittent-endurance fitness on match performance in young male soccer players. *J Strength Cond Res*. 2009;23(7):1954–1959. PubMed doi:10.1519/JSC.0b013e3181b7f743
64. Edwards AM, Clark N, Macfadyen AM. Lactate and ventilatory thresholds reflect the training status of professional soccer players where maximum aerobic power is unchanged. *J Sports Sci Med*. 2003;2(1):23–29. PubMed
65. di Prampero PE, Fusi S, Sepulcri L, Morin JB, Belli A, Antonutto G. Sprint running: a new energetic approach. *J Exp Biol*. 2005;208(Pt 14):2809–2816. PubMed doi:10.1242/jeb.01700
66. Stevens TG, De Ruiter CJ, Van Maurik D, Van Lierop CJ, Savelsbergh GJ, Beek PJ. Measured and estimated energy cost of constant and shuttle running in soccer players. *Med Sci Sports Exerc*. 2015;47(6):1219–1224. PubMed doi:10.1249/MSS.0000000000000515
67. Williford HN, Olson MS, Gauger S, Duey WJ, Blessing DL. Cardiovascular and metabolic costs of forward, backward, and lateral motion. *Med Sci Sports Exerc*. 1998;30(9):1419–1423. PubMed
68. Colby MJ, Dawson B, Heasman J, Rogalski B, Gabbett TJ. Accelerometer and GPS-derived running loads and injury risk in elite Australian footballers. *J Strength Cond Res*. 2014;28(8):2244–2252. PubMed doi:10.1519/JSC.0000000000000362
69. Hulin BT, Gabbett TJ, Lawson DW, Caputi P, Sampson JA. The acute:chronic workload ratio predicts injury: high chronic workload may decrease injury risk in elite rugby league players. *Br J Sports Med*. 2016;50(4):231–236. PubMed doi:10.1136/bjsports-2015-094817
70. Boyd LJ, Ball K, Aughey RJ. The reliability of MinimaxX accelerometers for measuring physical activity in Australian football. *Int J Sports Physiol Perform*. 2011;6(3):311–321. PubMed doi:10.1123/ijspp.6.3.311
71. Kelly SJ, Murphy AJ, Watsford ML, Austin D, Rennie M. Reliability and validity of sports accelerometers during static and dynamic testing. *Int J Sports Physiol Perform*. 2015;10(1):106–111. PubMed doi:10.1123/ijspp.2013-0408
72. Barrett S, Midgley A, Lovell R. PlayerLoad: reliability, convergent validity, and influence of unit position during treadmill running. *Int J Sports Physiol Perform*. 2014;9(6):945–952. PubMed doi:10.1123/ijspp.2013-0418
73. Barrett S, Midgley A, Reeves M, et al. The within-match patterns of locomotor efficiency during professional soccer match play: implications for injury risk? *J Sci Med Sport*. 2016;19(10):810–815. PubMed
74. Barrett S, Midgley AW, Towlson C, Garrett A, Portas M, Lovell R. Within-match PlayerLoad patterns during a simulated soccer match: potential implications for unit positioning and fatigue management. *Int J Sports Physiol Perform*. 2016;11(1):135–140. PubMed doi:10.1123/ijspp.2014-0582
75. Cormack SJ, Mooney MG, Morgan W, McGuigan MR. Influence of neuromuscular fatigue on accelerometer load in elite Australian football players. *Int J Sports Physiol Perform*. 2013;8(4):373–378. PubMed doi:10.1123/ijspp.8.4.373
76. Gallo TF, Cormack SJ, Gabbett TJ, Lorenzen CH. Pre-training perceived wellness impacts training output in Australian football players. *J Sports Sci*. 2016;34(15):1445–1451. PubMed
77. Chambers R, Gabbett TJ, Cole MH, Beard A. The use of wearable microsensors to quantify sport-specific movements. *Sports Med*. 2015;45(7):1065–1081. PubMed doi:10.1007/s40279-015-0332-9
78. Gabbett T, Jenkins D, Abernethy B. Physical collisions and injury during professional rugby league skills training. *J Sci Med Sport*. 2010;13(6):578–583. PubMed doi:10.1016/j.jsams.2010.03.007
79. Gastin PB, McLean OC, Breed RV, Spittle M. Tackle and impact detection in elite Australian football using wearable microsensor technology. *J Sports Sci*. 2014;32(10):947–953. PubMed doi:10.1080/02640414.2013.868920
80. McNamara DJ, Gabbett TJ, Chapman P, Naughton G, Farhart P. The validity of microsensors to automatically detect bowling events and counts in cricket fast bowlers. *Int J Sports Physiol Perform*. 2015;10(1):71–75. PubMed doi:10.1123/ijspp.2014-0062
81. Beanland E, Main LC, Aisbett B, Gastin P, Netto K. Validation of GPS and accelerometer technology in swimming. *J Sci Med Sport*. 2014;17(2):234–238. PubMed doi:10.1016/j.jsams.2013.04.007
82. Marsland F, Lyons K, Anson J, Waddington G, Macintosh C, Chapman D. Identification of cross-country skiing movement patterns using micro-sensors. *Sensors (Basel)*. 2012;12(4):5047–5066. PubMed doi:10.3390/s120405047
83. Adelsberger R, Tröster G. Experts lift differently: classification of weight-lifting athletes. In *2013 IEEE International Conference on Body Sensor Networks (BSN)*. 2013; Cambridge, MA: IEEE. doi:10.1109/BSN.2013.6575458
84. Ahmadi A, Rowlands D, James D. Towards a wearable device for skill assessment and skill acquisition of a tennis player during the first serve. *Sports Technol.* 2009;2(3-4):129–136. doi:10.1080/19346182.2009.9648510
85. Lai DTH, Hetchl M, Wei X-C, Ball K, Mclaughlin P. On the difference in swing arm kinematics between low handicap golfers and non-golfers using wireless inertial sensors. *Procedia Eng*. 2011;11:219–225. doi:10.1016/j.proeng.2011.05.076
86. Koda H, Sagawa K, Kuroshima K, Tsukamoto T, Urita K, Ishibashi Y. 3D measurement of forearm and upper arm during throwing motion using body mounted sensor. *J Adv Mech Des Syst Manuf*. 2010;4(1):167–178.