Title: The use of mobile applications to collect data in sport, health and exercise science: a narrative review

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## Abstract

Mobile devices are ubiquitous in the population, and most have the capacity to download applications (apps). Some apps have been developed to collect physiological, kinanthropometric and performance data, however the validity and reliability of such data is often unknown. An appraisal of such apps is warranted as mobile apps may offer an alternative method of data collection for practitioners and athletes with money, time and space constraints. This article identifies and critically reviews the commercially available apps that have been tested in the scientific literature, finding evidence to support the measurement of resting heart through photoplethysmograpy, heart rate variability, range of motion, barbell velocity, vertical jump, mechanical variables during running, and distances covered during walking, jogging and running. The specific apps with evidence, along with reported measurement errors are summarised in the review. Whilst mobile apps may have the potential to collect data in the field, athletes and practitioners should exercise caution when implementing them into practice as not all apps have support from the literature, and the performance of a number of apps have only been tested on one device.

**Key words:** Apps, testing, field testing, technology

## Introduction

Physiological and kinanthropometric measurements are an essential part of sport and exercise science as they can be used to monitor, evaluate and develop training programmes. Testing conditions can be tightly controlled under laboratory settings, with a number of tests that can be reproduced to relatively known degrees of accuracy with documentation of reliability testing. A possible limitation of these tests is the absence of ecological validity. Practitioners often rely upon field tests to measure and evaluate performance, either by choice to enhance familiarity and ecological validity for the athlete, or due to time, space, or facility constraints. Maximising the portability of equipment needed in the field would help the practitioner, and advances in technology means that smaller technologies are capable of much more. A recent paper from Cardinale and Varley (17) reviewed wearable technologies to monitor training, such as global positioning system (GPS) units, heart rate monitors, and accelerometers. However, some technologies do not require wearables, only the mobile device itself to collect data through downloadable applications (apps). With some of the most recent advances it is not unfathomable that coaches can collect the majority of their data using only their mobile device. However, the validity and reliability of this data can often be unknown. The purpose of this review is to critically appraise the literature in this area and identify variables that can be measured using commercially available apps on a mobile device.

## Capacity for apps to collect physiological and kinanthropometric data

In terms of collecting physiological data mobile devices can be used in two primary ways; (i) by acting as the data logger and interface for a peripheral attachment, and (ii) using the external sensors (e.g. microphone, camera) and internal processors of the device itself to collect and interpret signals. It is beyond the scope of this review to comment on the engineering of the methods in depth, instead the focus of this section is to review the validity and practical use of the latter method i.e. collection and interpretation using only the mobile device.

**Heart rate measurement**

Heart rate is a fundamental physiological measurement in the sport, health and exercise sciences. The criterion, or 'gold-standard', remains to be the electrocardiogram (ECG), which can be impractical in the field. A number of telemetry devices have been validated against the ECG for use in more practical situations (81, 108), however these devices also come with cost implications for multiple units, and the placement of a chest strap may be deemed intrusive by some clients. Furthermore the requirement for extra hardware may limit widespread use (98). This may particularly be the case in more health related environments such as fitness centres and rehabilitation units. Practitioners in these areas may only have manual palpation methods available to them, which have been demonstrated to be inaccurate (41, 59). It is in such cases that the technology within ubiquitously available mobile devices may be of benefit. The most simplistic of apps to facilitate heart rate measurement act in a similar way to a metronome, whereby the screen is tapped every time a pulse has been palpated. This method is presumably designed to reduce error by separating the tasks of palpating and counting. However Peart *et al*. (83) found that one such app on an iOS iPad mini 2 (*'Tap the Pulse'* by Orangesoft LLC) had greater discrepancy to telemetry measurements when compared to manual methods ($r^2$ = 0.636, CV = 7% and $r^2$ = 0.851, CV = 3% respectively).

More advanced measurements use technology known as photoplethysmograpy (PPG). PPG is the technology currently used in finger tip pulse oximeters, and works on the basis that when capillaries are filled with blood light is obstructed, and more light can pass through as blood is retracted. Pelegris *et al* (85) explain that it is this change in average brightness that acts as the signal for the device to interpret and extract heart rate readings from. The same authors looked to validate their technology that calculated heart rate taken from a stream of picture frames when the finger was held against the camera lens and flash of a HTC Tatoo (Android 1.6) mobile phone, compared to a pulse oximeter. Unfortunately the main focus of this paper appeared to be the description of the technology and there is little information about how the technology was actually validated. The raw data is provided in the paper and the correlation between methods has been calculated as moderate ($r$ = 0.6) with an average four beats per minute (bpm) difference between methods. Popescu *et al* (90) and Losa-Iglesias *et al* (62) both assessed the capabilities of two commercially available apps that worked on the same premise of applying the fingertip to the device's camera and flash. Popescu al. (90) compared *'Cardiowatch'* by Radu Ionescu on an iPhone to an ECG machine, and Losa-Iglesias *et al* (62) compared *'Heart Rate Plus'* by AVDApps on a Samsung Galaxy Note phone to a pulse oximeter, with both studies reporting a typical difference of ± 3-4 bpm between measurement methods.

Whilst the contact PPG technology seems to be able to measure resting heart rate relatively accurately, data from Wackel *et al* (109) suggest that error may increase as heart rate increases. These authors reported resting values measured with *'Instant Heart Rate'* by Azumio and *'Heart Beat Rate'* by Bio2imaging on an iPhone 5 to be within ± 4 bpm of an ECG measurement (r = 0.99) in paediatric patients, similar to the afore mentioned work (62, 85, 90). However when the apps were used during a period of tachycardia (156 - 272 bpm) the average difference compared to an ECG increased to 18 bpm (up to 47 bpm), and the correlation reduced to $r = 0.56$. This has obvious implications for sport and exercise as heart rate measurements are likely to take place after exercise. It should be considered though that the use of such technology post-exercise may be most likely to be used following submaximal predictor tests, where the heart rate is unlikely to be as high as those observed by Wackel *et al* (109). Whilst the tachycardic range witnessed by Wackel *et al* (109) was from 156 bpm, the majority were greater than 200 bpm. Ho *et al* (51) measured heart rates in 126 children admitted to hospital on four different apps on a iPhone 4S at the earlobe and fingertip alongside an ECG machine. The heart rates from the apps were more closely correlated with the ECG at the earlobe rather than finger, with correlations ranging from $r^2 = 0.215$ to 0.857. App A considerably outperformed the other three apps with anomalous results appearing to start at approximately 160 bpm. Unfortunately the authors did not provide the names of the apps tested. The only known study to test contact PPG technology on mobile devices after exercise was conducted by Mitchell *et al* (70). Participants had their heart rate measured at rest and after a 1-minute step test, so replicating the conditions under which the technology is perhaps most likely to be used. Measurements were taken using the same '*Instant Heart Rate'* by Azumio app used by Wackel *et al* (109) on an iOS and Android phone, and a Polar telemetry chest strap. Intraclass correlation coefficients with the telemetry method (with 95% confidence intervals) were 0.97 (0.95 - 0.98) and 0.95 (0.92 - 0.96) at rest, and 0.90 (0.86 – 0.93) and 0.94 (0.91 – 0.96) after exercise for the iOS and Android phones respectively. The authors concluded that both platforms could be used with confidence, however when viewing the Bland-Altman plots the error again appears to increase as heart rate increases.

Kong *et al* (56) have suggested that PPG may be made more accurate by using contactless methods, as the contact force on the sensor may affect the waveform of the signals. Contactless PPG using a webcam on a laptop has been described by Poh *et al* (89). This technology works on a similar principle to the contact PPG, but instead observes video recordings of the face. A number of freely available apps make use of this contactless PPG method and instruct users to hold the device's camera in front of their face until a reading has been taken. Peart *et al* (83) investigated two contactless PPG apps at rest on an iPad mini 2, '*What's my heart rate'* by ViTrox Technologies and '*Cardiio*' by Cardiio Inc, reporting average differences compared to a Polar telemetry monitor of one and two beats per minute, and correlations of $r^2 = 0.918$ and $r^2 = 0.646$ respectively. In a subsequent study '*What's my heart rate'* was used to collect heart rates after a 1-minute step test (84). Average heart rate after the test was measured as 129 bpm using a Polar telemetry strap, but only 84 bpm using the app. Furthermore when the heart rates were used to estimate aerobic capacity, average values were 17% higher when using the app.

Heart rate alone may only be of limited interest to some practitioners, and many may instead be more interested in the regularity of the heart beat. An abstract with limited information from Sardana *et al* (98) reports high sensitivity and reliability for an iPhone app to identify atrial fibrillation (AF). McManus and colleagues describe apps that can identify AF as well as premature atrial contractions (PAC) and premature ventricular contractions (PVC) (65, 66). Whilst such measurements may not be of widespread interest to sport and exercise scientists, the ability to determine regularity will be, particularly when considering measurements such as heart rate variability (HRV) for monitoring responses and adaptation to training (87). At present there is limited means to measure HRV using the mobile device alone, although some studies have described valid measurement with chest strap or fingerpad peripherals by ithlete (HRV Fit Ltd) that attach to a mobile phone (34, 49), sensitive enough to track changes over a period of three weeks (35). However some self contained apps are currently being developed. Scully *et al* (100) describe an app that can take 720x480 pixel resolution video recordings that can then be analysed for HRV using Matlab, and Guede-Fernandez *et al* (45) have developed a non-commercially available app for HRV. Interestingly, the standard deviation of the beat to beat error differed between devices (Motorola Moto X and Samsung S5), identifying potential transferability issues between research and practice. The only known commercially available HRV app present in the literature is *'HRV4Training'* by Marco Altini. This app uses the device's camera to obtain PPG data from the user's fingertip, from which peak to peak intervals are used to identify the route mean square of the successive differences (rMSSD) and calculate HRV (1). A recent paper in press has described the validation of the app against an ECG machine (88), and it has been demonstrated that measurements from the *'HRV4Training'* App are sensitive enough to detect changes in HRV following intense training (1). Plews *et al.* (88) did not provide the name of the device used to validate the app against an ECG, but did specify a frame rate requirement of 30 Hz. Furthermore two studies implementing the app have collected data from 532 (2) and 797 (1) participants respectively, demonstrating that it offers real potential to collect large amounts of free-living data outside of laboratory settings.

**Respiratory measurements**

Folke *et al*. (36) suggest that tidal volume (VT) and respiratory rate (RR) are two basic vital signs breathing monitoring should provide. Methods of recording VT typically includes the use of a spirometer that can be either portable (e.g. hand-held) or much larger (e.g. simple float). RR can be obtained by simple human observation or via more sophisticated procedures such as breath-by -breath gas analysis or transthoracic impedance. Whilst Reyes *et al*. (91) acknowledge the existence of clinical measures of VT and RR, they also highlight the limitations and disadvantages of existing equipment, in particular the limited access outside of clinical and / or research settings. Further limitations in existing methods include high costs, specialist personnel and lack of portability (79, 91). Respiratory function can be assessed through numerous ways via the different smartphone hardware including the camera, microphone, and accelerometer.

Reyes *et al*. (91) used the frontal camera of a HTC One M8 smartphone with the Android v4.4.2 (KitKat) operating system to acquire a chest movement signal which demonstrated a strong relationship ($r^2 > 0.9$) with a spirometer when recording VT. Nam *et al*. (79) demonstrated similar findings, concluding accurate estimation of breathing rate on the same HTC device. However, although Reyes *et al*. (91) did not find statistically-significant bias in recording VT, the authors questioned whether the error estimate was acceptable for home use. Although the investigation demonstrated reliability and validity in estimating VT and RR, there was still the presence of limitations inherent to contactless optical procedures. Motion artifacts are present in any contactless / noncontact optical procedure of data acquisition and previous research has demonstrated artifact removal improves estimation of respiratory rate (101, 105). Furthermore, Nam *et al*. (79) suggested that clothing affected the video signal, for example plain designs compared to striped or non-uniform designs produced smaller relative changes in recorded chest and abdominal movements. Beyond the limitations of the data acquisition and processing, noncontact optical procedures in estimating respiratory parameters lack practical applicability to a more general use setting.

Reyes *et al.*´s (91) procedure requires calibration per individual use with a spirometer, and a qualitative observation of changes in VT is recommended if calibration instrumentation is not available. Reyes *et al*. (92) did extend their work to demonstrate the efficacy of smartphone use when calibrated with a low-cost incentive spirometer, whereby individuals inspired to a target volume. However, at this stage, it could be argued that there is currently a redundancy in using a smartphone to record respiratory parameters whilst there is a need to calibrate using additional equipment. Furthermore, Reyes *et al*. (92) themselves suggest "the development of an inexpensive and portable breathing monitoring system for on-demand VT and RR estimation capabilities is still pending for the general population". Therefore technically, Reyes *et al*. (91, 92) have developed software for a smartphone to record respiratory data independently, but reliability is questionable without the use of additional hardware.

Both Reyes *et al*. (91) and Nam *et al*. (79) have demonstrated the valid and reliable use of smartphone hardware to record parameters of lung function. However, in keeping with the theme of this paper, neither author has investigated the validity and reliability of a specific smartphone software application that is commercially available for public use. There are currently a range of apps available that provide estimations of RR obtained from tapping on the screen of a smartphone or tablet device, similar to apps such as *'Tap the Pulse'* (Orangesoft LLC) for determining heart rate. Current apps available that utilise this procedure include *'RRate'* (PART BC Children's), *'Medtimer'* (Tigerpixel), and *'Medirate'* (MobileMed Sarl). Karlen *et al*. (55) assessed the accuracy of the *'RRate'* app by showing pre-recorded videos to hospital staff, and asking them to tap on the screen of an iPod touch ($3^{rd}$ generation) every time they witnessed the child on the screen breathe. The purpose was to enhance efficiency and accuracy of RR estimations by replacing absolute counts with continuous time intervals. It was reported that the use of the app reduced collection time from 60 seconds to $8.1 \pm 1.2$ seconds, with a typical error of only 2.2 breaths per minute.

**Anthropometry and range of motion**

Body composition has been assessed in a number of ways including Hydrostatic Weighing (HW) (21) and Dual Energy X-ray Absorptiometry (DXA/DEXA) (53) with some disagreement on the gold standard. There is, however, agreement that these methods present difficulties such as expense, time-consumption, access, and portability (54, 63). Such equipment is typically restricted to University laboratories and research settings, and therefore difficult to access for some practitioners such as primary healthcare workers, nutritionists, fitness instructors and personal trainers.

With developments in technology, comes the potential for more cost-effective solutions in measuring and assessing body composition. Farina *et al*. (29) consider 2D imaging, using frontal and lateral images obtained from a standard digital camera, an alternative to costly 3D systems. Using 2D images to provide accurate anthropometric data is not a new development (52). More recent applications of digitizing 2-dimensional images to provide anthropometric include providing hand measurements for the production of work gloves (46). However these applications of 2-dimensional images only provide surface measurements and do not make inferences on tissue composition. Farina *et al*. (29) examined the use of a smartphone built-in camera to obtain digital whole-body images to estimate human body composition, finding a negligible ($p = 0.96$) 0.02 kg and 0.07 kg difference in estimated fat mass between the app and DXA in females and males respectively (Android version 4.2.2 on a Huawei G730 smart phone (resolution 540 × 960 pixels or 51.8 megapixels) or iOS 9.2 on an iPhone 5s (resolution 1136 × 640 pixels or 72.7 megapixels). The study utilised bespoke, in-house, software as a proof of concept to suggest their findings were 'promising' for the use of a smartphone application to monitor bodyfat. LeanScreen$^{TM}$ (Postureco, Trinity, Florida, USA) is a software application that uses two-dimensional (2D) photographs taken using a smartphone or tablet to estimate percentage bodyfat by digitizing a series of girths. Shaw *et al*. (102) assessed the reliability of this software application on an iPad mini against skinfold measurements and bio-electrical impedance which were considered as other field measures comparable to use of a tablet device (i.e. cost, portability). There were no significant differences between the methods for estimated percentage body fat (%BF) ($p = 0.818$) and intra-class correlation coefficients demonstrated the reliability of each method to be good ($\geq$0.974). However, the absolute reproducibility, as measured by coefficient of variance and typical error of measurement, was much higher in skinfold measurements and bio-electrical impedance ($\leq$1.07 and $\leq$ 0.37

respectively) compared with LeanScreen™ (6.47 % and 1.6%). The authors concluded that the LeanScreen™ smartphone / tablet application is not suitable for a single, one-off, measurement of %BF and that individual variance should be measured to determine minimal worthwhile change.

Previous studies have investigated the use of smartphones in more applied anthropometry contexts such as posture assessment. PostureScreen Mobile® is a smartphone application, from the same company that produced LeanScreen® (PostureCo Inc., Trinity, FL, USA), that assesses posture using 2-dimensional photographs taken by smartphone or tablet. Boland *et al*. (10) examined intra- and inter-rater agreement of PostureScreen Mobile® in assessing standing static posture on an iPad . The authors concluded to have found acceptable levels of agreement for three different examiners of varying experience. However, the investigators consisted of a doctor of physical therapy (US licenced physiotherapist) and two undergraduate students with the authors making no reference to their undergraduate program of study. Of the 13 postural measures that PostureScreen Mobile® provides (head shift lateral, head shift longitudinal, head tilt, shoulder shift lateral, shoulder shift longitudinal, shoulder tilt, ribcage shift, hip shift lateral, hip shift longitudinal, hip tilt, head weight, effective head weight, and knee shift), inter-rater agreement (ICC) ranged from 0.10 - 1.00 in the fully clothed condition and from 0.26 - 1.00 in the minimal clothing condition. Boland *et al*. (10) rationalised their investigation by suggesting the measures from the app would only have value if they could be reliable across multiple trials. However they only assessed intra-rater agreement for the doctor of physical therapy. Considering that PostureScreen Mobile® is commercially available to public, the reliability of this app can be questioned based on the investigation by Boland *et al*. (2016).

In relation to specific postural anomalies, Driscoll *et al*. (27) used an iPhone 4 to examine the reliability of Scolioscreen  (Spinologics Inc., Montreal, Canada) to assess adolescent idiopathic scoliosis  by measuring maximum angle of trunk inclination (ATI). The *'Scolioscreen'* app is additional to the actual Scolioscreen which is a scoliometer design to house any smartphone contains inclinometer hardware. The manufacturers state that the Scolioscreen can be combined with any app that measure inclinations. However Driscoll *et al*. (27) investigated the reliability of the scolioscreen-smartphone combination as well as the smartphone alone. In all three investigators used (Spine Surgeon, Nurse, Patient Parent), intra- and inter-observer reliability was higher (0.94-0.89) with the scolioscreen-smartphone combination than the smartphone alone (0.89-0.75). Furthermore the smartphone alone demonstrated lower consistency (ICC = 0.86) with the gold standard (Spine Surgeon using standard scoliometer) than the scolioscreen-smartphone (ICC = 0.95). At this stage, using a smartphone independent of additional equipment does not offer an effective alternative for examining scoliosis.

The validity and reliability of goniometric data obtained using smartphone photography has previously been examined. *'DrGoniometer'* (CDM, Italy) has been shown to validly measure flexion at the elbow and knee (31, 33) as well as external rotation of the shoulder (71). In addition to providing reliable and valid measures of joint range of motion, photographic-based apps are advantageous by inevitably provide a lasting record of the measurement i.e. the actual photo (69). Although Ferriero *et al*. (32) propose the potential applications of photographic-based apps in telemedicine, Milani *et al*. (69) argue apps of this type have the same limitations of standard digital photography such as handling instability and imprecision. Therefore photographic-based apps offer nothing alternative to a standard digital camera. Furthermore conventional long-arm goniometers can be purchased at the or lower cost to *'DrGoniometer'*. Given that photographic-based goniometry apps can not record range of motion in dynamic conditions in the same way that conventional long-arm goniometers can not, it is argued that this type of smartphone application does not offer a more practical nor cost-effective solution to existing instruments.

Accelerometer-based apps may provide an effective alternative to a conventional long-arm goniometer. These apps utilise the triaxial accelerometer hardware built into smartphones, traditionally serving as position sensors for the use in video games by measuring inclination of the smartphone device (82). Ockendon and GIlbert (82) have demonstrated high reliability ($r$ = 0.947) and validity of a smartphone accelerometer-based app (iPhone 3GS). Furthermore, the authors also found greater inter-rater reliability compared to a traditional goniometer. Given that most practitioners that typically assess range of motion (e.g. physiotherapists, strength and conditioning coaches) would do so independently, it can be argued that inter-rater reliability is not relevant to this context. However the same study did demonstrate superior intra-rater reliability compared to the traditional method, offering support for accelerometer-based apps as a viable alternative to traditional methods of goniometry. Milani *et al*. (69) argue that accelerometer-based, photographic-based, and magnetometer-based apps all possess the same limitation in that they can only measure range of motion in static conditions. Therefore for smartphone applications to be considered as an effective alternative, they must be able to validly and reliably measure angular movement in dynamic conditions e.g. active rotations. More recently Bittel *et al*. (9) used the accelerometer of an iPhone 4 to measure extension and flexion movements concurrently with an isokinetic dynamometer at a range of different speeds (30, 60, 90, 120, and 150°/s). The authors demonstrated limits of agreement of 2° between the smartphone and the dynamometer.

To summarise, previous investigations have demonstrated inter-and-intra-rater reliability as well as validity of photography-based, accelerometer-based, and magnetometer-based goniometer apps. Whilst the review by Milani *et al*. (69) provides a comprehensive discussion on the efficacy of currently available smartphone apps, a more up-to-date review is required now that more recent investigations such as Bittel *et al*. (9) have demonstrated validity and reliability of the iPhone accelerometer to measure angular changes in dynamic conditions. However there is currently no app commercially available with this specific function

Table 1. Summary of apps for taking physiological and kinanthropometric measurements

| | |
|---|---|
| *At current, what physiological and anatomical measurements can apps take?* | Commercially available apps using contact and contactless PPG technology can accurately measure resting heart rate within ± 4bpm. Some non-commercially available apps are able to detect some irregularities at rest. Most recently, the HRV4Training App has been validated to measure heart rate variability against an ECG (trivial standardised difference of 0.10; 90% CI 0.08, 0.13). Commercially available apps can validly and reliably measure range of motion during static conditions. This can be done using either the smartphone's camera, accelerometer, or magnetometer. |
| *What measurements can apps currently not take?* | The accuracy of PPG apps reduces significantly at higher heart rates associated with exercise. For respiratory measurements, existing research has only validated the use of smartphone hardware in conjunction with bespoke non-commercially available software. There are no commercially available apps that measure range of motion during dynamic conditions. Research into the estimation of body composition is in its early stages, but demonstrates potential. |
| *Do the currently available apps offer anything beyond traditional measurements?* | If used with care and interpreted correctly PPG Apps may be appropriate in some situations when telemetry is unavailable, particularly at rest. The HRV app provides an alternative to the ECG for practitioners working outside of the laboratory. Accelerometer-based apps may offer increased inter-and-intra-reliability of measures of range of motion compared to a standard goniometer. |

## Capacity for apps to analyse physical performance

One of the main problems that strength and conditioning coaches face is how to objectively quantify the physical capabilities of their athletes (37, 57). Measuring physical performance is, indeed, a key part of any training program since it allows the practitioner to monitor and adjust workloads (44, 76), analyse fatigue (47, 106), detect talents (38, 72), identify weaknesses (97), or prevent injuries (16, 67, 68). Thus, a common practice when designing strength and conditioning programs is to measure specific variables of interest that could help in the prescription of the training stimulus (42, 44, 57, 76); however, the technology and expertise required to do so is often expensive and non-user-friendly, especially for coaches or teams outside big organizations or Universities. For this, the rise of smartphones, which currently include several sensors specifically designed to measure physical performance (like heart rate monitors, GPS or accelerometers) are gaining popularity in the fitness and health community (4, 11, 107). For example, fitness and health apps are among the top fitness trends in the list elaborated by the American College of Sports Medicine (107). However, just a few of the thousands of fitness apps available are scientifically validated (11). Thus, the purpose of this section is to provide an updated review of some of the most relevant studies that have analyzed the validity and reliability of smartphone apps for the measurement of several variables related to physical performance.

**Maximal strength**

Resistance training prescription is based on the well-known 1-Repetition maximum (1-RM) paradigm, by which intensities are designed as a percentage of the maximal load the athlete can lift just once (57, 99). However, measuring the 1-RM requires the performance of a maximal lift which may not be appropriate for all populations, especially those with little expertise in lifting heavy weights since it could lead to inaccurate results and might increase the risk of injuries (44).

Several alternatives, such as performing repetitions to failure or using the rate of perceived exertion has been used to predict the 1-RM with submaximal loads (26, 77). However, it has been advocated that the most accurate methodologies consist of measuring the speed of the barbell. This is due to the fact that it has been extensively demonstrated that there is a very strong ($r^2$>0.97) relationship between the load in terms of %1-RM and the velocity at which each load is lifted (18, 76, 86). Thus, a new resistance training paradigm, often described as velocity based training, has emerged based on systematic measurements of barbell velocity to adjust and prescribe training intensities, since each %1-RM has a specific velocity range (22, 44, 76). The gold standard for the measurement of barbell velocity are high-frequency linear transducers (23, 76); however its cost, above $2,000 in most cases, prevent its use in small organizations or clubs with little resources.

Trying to address this limitation, an iOS app named *'PowerLift'* has been recently validated for the measurement of barbell velocity in the bench press exercise in resistance trained males (5). To do this, authors measured several repetitions in a group of powerlifters with a linear transducer (working at 1kHz) and the *'PowerLift'* app on an iPhone 6 (iOS 9.3.2) simultaneously, and then compared the results. *'PowerLift'*, which consists of the recording and ulterior analysis of a slow-motion video of the lift thanks to the high-speed camera on the most recent iOS devices, was significantly correlated with the linear transducer (r = 0.94) and showed a small standard error of estimate (SEE = 0.008m/s) in the measurement of barbell velocity. Moreover, there were no significant differences between the 1-RM predicted by the velocity measured with the linear transducer or the app, meaning that *'PowerLift'* could be a less expensive, yet accurate and valid alternative for the estimation of maximal strength.

**Muscular power or impulse: Vertical jump height**

The measurement of vertical jump height has been used extensively in the literature to assess muscle power, detect talents, or analyse neuromuscular fatigue (6, 23, 58, 95). Considering that vertical jumping is an essential ability in many sports (4, 25, 95), its measurement is often a key part of any performance analysis. Several approaches have been proposed to measure the height an athlete can reach during a vertical jump (7, 30, 40, 95), although the most accurate typically consist of the measurement of either the take-off velocity or flight time of the jump. This is since these parameters can calculate the vertical displacement of the centre of mass using well-known Newtonian equations (95). Whilst force platforms are often considered the gold standard for the measurement of vertical jumps by measuring the take-off velocity of the athlete (23, 95), several systems based on the detection of the flight time (such as infrared platforms) have become popular in the strength and conditioning community since they are less expensive, more portable and can still provide very accurate measures of jump height (4, 7, 43). One of those systems is an iPhone app (*'My Jump'*) which measures the flight time of the jump thanks to the slow-motion recording capabilities on the iPhone 5s and later (4, 103). With a simple video-analysis in which the take-off and landing of the jump are visually detected by the user within the app, *'My Jump'* calculates the flight time of the jump in an accurate, valid and reliable way. The performance of the app has been confirmed widely in the literature over recent years, showing levels of correlation above 0.96 and a systematic bias less than 10 mm in comparison with reference systems (4, 39, 104).

**Human locomotion: Running and sprinting**

The analysis of human locomotion is of great interest for both performance and injury prevention purposes (68, 74, 80, 96). For example, several mechanical variables such as ground contact time, leg stiffness, or the horizontal force applied to the ground has been shown to be related with running and maximal sprinting performance (73, 93, 96). Moreover, studies have suggested that the asymmetries between legs in some of these variables could be used as a relevant indicator related to risk of injury (12, 50). As with the performance variables described above, the measurement of running and sprinting mechanics has usually required advanced measurement systems such as instrumented treadmills, force platforms, timing gates or radar guns (15, 75, 94); expensive technology which most coaches do not have access to. Using the same approach than with the jumping and resistance training apps mentioned above, two new apps also based on high-speed video-analysis were recently validated for the measurement of running and sprinting mechanics on an iPhone 6 (iOS 9.2.1, 240 frames per second) (3, 94). The first one, *'Runmatic'*, was tested against an infrared platform for the detection of contact and flight times during running at several speeds ranging 10-20km/h in male runners (3). Moreover, the app made use of some validated spring-mass model equations that allow the calculation of different mechanical variables based on contact time, flight time and simple anthropometrics (74). The app was shown to be valid and reliable for the measurement of leg stiffness, vertical oscillation of the centre of mass, maximal force applied to the ground, and stride frequency ($r$ = 0.94-0.99, bias = 2.2-6.5%). The second one, *'My Sprint'*, was also shown to be highly valid and reliable for the measurement of 30 m sprint time and the production of horizontal force, velocity, and power in male sprinters in comparison with timing gates and a radar gun, with no significant differences between devices (94). Thus, these apps allow the practitioner to measure important variables related with running and maximal sprinting without the need of any advanced instruments.

**Distance tracking using GPS and accelerometer sensors**

When talking about running, probably the most popular variable in the sports technology industry is the distance covered using GPS signals (and, consequently, running pace) (14, 28, 48). Several wearable devices (mainly watches) have been used both in practice and research to measure running distances (13, 78), although the inclusion of GPS sensors on most smartphones in recent years has catalysed the creation of apps which take advantage of that technology to track distances and running pace (24). In fact, distance trackers are among the top twenty fitness trends for 2017 (107); however, there is a lack of evidence regarding their validity and reliability. One recent study analysed the validity and reliability of an iOS app designed to measure distances during running by using the GPS included in the iPhone smartphones (8). To do this, researchers had subjects run on a 400 m track for a total of 2,400 m while wearing an iPhone in an armband, and then compared the values of distance and speed obtained by the app with the actual values. The app underestimated both distance and speed by 3-4%, meaning an absolute difference of approximately 100 m or 0.7 km/h. However, the good test-retest reliability observed (i.e. comparing values in two separate trials) and the relatively low bias between the app and the actual distance made the authors conclude that the app might be appropriate to track running in the general population, although it might be not adequate for trained athletes.

Another widespread variable related to walk or running is step count (20, 64). Specifically, it has been proposed that a minimum count of 10,000 steps per day is associated with good levels of daily physical activity and health status (20, 64). For this, many of the most popular wearable devices available in the market are focused in steps tracking using acceleration data to provide users with information about their step count (11, 19, 60). Of course, since smartphones include accelerometers, literally thousands of step tracking apps have been developed to count the steps of the users without the use of external devices. However, a recent study has showed that these apps lack accuracy in comparison with a professional pedometer, probably due to the low quality of the accelerometers included in most smartphones (61). In this investigation, researchers compared a reference pedometer to three Android based step tracking apps ('*Runtastic'*, *'Pacer Works'*, *'Tayutau'*) on a Samsung Galaxy S4 GT-I9500 under laboratory conditions, and each participant's own respective smartphone in a free-living setting. The three apps significantly under or overestimated the steps counting by 16-50% and showed low levels of agreement with the reference method ($r < 0.5$), so the researchers concluded that this kind of app cannot be recommended for step tracking in their current state of development.

Table 2. Summary of apps for analysing physical performance

| | |
|---|---|
| *At current, what physical performance measurements can apps take?* | Barbell velocity (standard error of estimate = 0.008 m/s), vertical jump (systematic bias of 10 mm), and different mechanical variables during running (leg stiffness, vertical oscillation of the centre of mass, maximal force applied to the ground, and stride frequency $r$ = 0.94-0.99, bias = 2.2-6.5%) using high-speed video analysis. Distances during walking, jogging or running using GPS signal can also be measured within 3-4% of reference values. |
| *What measurements can apps currently not take?* | Measure speed/acceleration during walking, jogging or running using GPS signal and daily steps. |
| *Do the currently available apps offer anything beyond traditional measurements?* | Affordability, transportability and ease of use. Apps are often designed with a user-friendly interface, which does not require great expertise in the biomechanics or physiology implied in the data processing. |

**Practical applications**

A summary of the currently available apps described in the scientific literature is available in tables 1 and 2 of this review. Mobile apps have the potential to transform data collection in the field, particularly for practitioners that face space, cost and time constraints. A number of apps have been validated to collect physiological and anatomical measurements such as heart rate and range of motion, and physical performance measurements such as vertical jump height, barbell velocity and contact times. However, practitioners and athletes should exercise caution and be critical when integrating apps into their training practices, as this review has identified some areas where research support is lacking. Furthermore, whilst the accuracy of some apps has been validated, their low cost commercial availability makes them widely available to a lay audience. Therefore, it is important that app developers consider implementing clear guidance on result interpretation for all potential users. A final consideration is the limited information on transfer between devices, due to the majority of papers testing the apps on a single platform, and the regular technological updates from manufacturers. Care has been taken in this review to provide as much information as possible about the device used in the described studies, and readers should make a judgment as to the appropriateness for their own device.

## Conflicts of interest

MADE ANONYMOUS.

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