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Citation: Peart, Daniel, Balsalobre-Fernández, Carlos and Shaw, Matthew (2019) The use of mobile applications to collect data in sport, health, and exercise science: a narrative review. *Journal of Strength and Conditioning Research*, 33 (4). pp. 1167-1177. ISSN 1064-8011

Published by: Lippincott Williams & Wilkins

URL: <http://doi.org/10.1519/JSC.0000000000002344>  
<<http://doi.org/10.1519/JSC.0000000000002344>>

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

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23 **Abstract**

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

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

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42 **Introduction**

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

58

59 **Capacity for apps to collect physiological and kinanthropometric data**

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

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## 69 **Heart rate measurement**

70

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

84

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

97 machine, and Losa-Iglesias *et al* (62) compared 'Heart Rate Plus' by AVDApps on a Samsung Galaxy Note phone  
98 to a pulse oximeter, with both studies reporting a typical difference of  $\pm 3-4$  bpm between measurement methods.

99

100 Whilst the contact PPG technology seems to be able to measure resting heart rate relatively accurately, data from  
101 Wackel *et al* (109) suggest that error may increase as heart rate increases. These authors reported resting values  
102 measured with 'Instant Heart Rate' by Azumio and 'Heart Beat Rate' by Bio2imaging on an iPhone 5 to be within  
103  $\pm 4$  bpm of an ECG measurement ( $r = 0.99$ ) in paediatric patients, similar to the afore mentioned work (62, 85,  
104 90). However when the apps were used during a period of tachycardia (156 - 272 bpm) the average difference  
105 compared to an ECG increased to 18 bpm (up to 47 bpm), and the correlation reduced to  $r = 0.56$ . This has obvious  
106 implications for sport and exercise as heart rate measurements are likely to take place after exercise. It should be  
107 considered though that the use of such technology post-exercise may be most likely to be used following  
108 submaximal predictor tests, where the heart rate is unlikely to be as high as those observed by Wackel *et al* (109).  
109 Whilst the tachycardic range witnessed by Wackel *et al* (109) was from 156 bpm, the majority were greater than  
110 200 bpm. Ho *et al* (51) measured heart rates in 126 children admitted to hospital on four different apps on a iPhone  
111 4S at the earlobe and fingertip alongside an ECG machine. The heart rates from the apps were more closely  
112 correlated with the ECG at the earlobe rather than finger, with correlations ranging from  $r^2 = 0.215$  to 0.857. App  
113 A considerably outperformed the other three apps with anomalous results appearing to start at approximately 160  
114 bpm. Unfortunately the authors did not provide the names of the apps tested. The only known study to test contact  
115 PPG technology on mobile devices after exercise was conducted by Mitchell *et al* (70). Participants had their heart  
116 rate measured at rest and after a 1-minute step test, so replicating the conditions under which the technology is  
117 perhaps most likely to be used. Measurements were taken using the same 'Instant Heart Rate' by Azumio app  
118 used by Wackel *et al* (109) on an iOS and Android phone, and a Polar telemetry chest strap. Intraclass correlation  
119 coefficients with the telemetry method (with 95% confidence intervals) were 0.97 (0.95 - 0.98) and 0.95 (0.92 -  
120 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  
121 respectively. The authors concluded that both platforms could be used with confidence, however when viewing  
122 the Bland-Altman plots the error again appears to increase as heart rate increases.

123

124 Kong *et al* (56) have suggested that PPG may be made more accurate by using contactless methods, as the contact  
125 force on the sensor may affect the waveform of the signals. Contactless PPG using a webcam on a laptop has been

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

135

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

155 *et al.* (88) did not provide the name of the device used to validate the app against an ECG, but did specify a frame  
156 rate requirement of 30 Hz. Furthermore two studies implementing the app have collected data from 532 (2) and  
157 797 (1) participants respectively, demonstrating that it offers real potential to collect large amounts of free-living  
158 data outside of laboratory settings.

159

## 160 **Respiratory measurements**

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

170

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



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

193

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

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209 **Anthropometry and range of motion**

210

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

217

218 With developments in technology, comes the potential for more cost-effective solutions in measuring and  
219 assessing body composition. Farina *et al.* (29) consider 2D imaging, using frontal and lateral images obtained  
220 from a standard digital camera, an alternative to costly 3D systems. Using 2D images to provide accurate  
221 anthropometric data is not a new development (52). More recent applications of digitizing 2-dimensional images  
222 to provide anthropometric include providing hand measurements for the production of work gloves (46). However  
223 these applications of 2-dimensional images only provide surface measurements and do not make inferences on  
224 tissue composition. Farina *et al.* (29) examined the use of a smartphone built-in camera to obtain digital whole-  
225 body images to estimate human body composition, finding a negligible ( $p = 0.96$ ) 0.02 kg and 0.07 kg difference  
226 in estimated fat mass between the app and DXA in females and males respectively (Android version 4.2.2 on a  
227 Huawei G730 smart phone (resolution  $540 \times 960$  pixels or 51.8 megapixels) or iOS 9.2 on an iPhone 5s (resolution  
228  $1136 \times 640$  pixels or 72.7 megapixels). The study utilised bespoke, in-house, software as a proof of concept to  
229 suggest their findings were 'promising' for the use of a smartphone application to monitor bodyfat. LeanScreen™  
230 (Postureco, Trinity, Florida, USA) is a software application that uses two-dimensional (2D) photographs taken  
231 using a smartphone or tablet to estimate percentage bodyfat by digitizing a series of girths. Shaw *et al.* (102)  
232 assessed the reliability of this software application on an iPad mini against skinfold measurements and bio-  
233 electrical impedance which were considered as other field measures comparable to use of a tablet device (i.e. cost,  
234 portability). There were no significant differences between the methods for estimated percentage body fat (%BF)  
235 ( $p = 0.818$ ) and intra-class correlation coefficients demonstrated the reliability of each method to be good  
236 ( $\geq 0.974$ ). However, the absolute reproducibility, as measured by coefficient of variance and typical error of  
237 measurement, was much higher in skinfold measurements and bio-electrical impedance ( $\leq 1.07$  and  $\leq 0.37$

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

241

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

257

258 In relation to specific postural anomalies, Driscoll *et al.* (27) used an iPhone 4 to examine the reliability of  
259 Scolioscreen (Spinologics Inc., Montreal, Canada) to assess adolescent idiopathic scoliosis by measuring  
260 maximum angle of trunk inclination (ATI). The 'Scolioscreen' app is additional to the actual Scolioscreen which  
261 is a scoliometer design to house any smartphone contains inclinometer hardware. The manufacturers state that the  
262 Scolioscreen can be combined with any app that measure inclinations. However Driscoll *et al.* (27) investigated  
263 the reliability of the scolioscreen-smartphone combination as well as the smartphone alone. In all three  
264 investigators used (Spine Surgeon, Nurse, Patient Parent), intra- and inter-observer reliability was higher (0.94-  
265 0.89) with the scolioscreen-smartphone combination than the smartphone alone (0.89-0.75). Furthermore the

266 smartphone alone demonstrated lower consistency (ICC = 0.86) with the gold standard (Spine Surgeon using  
267 standard scoliometer) than the scolioscreen-smartphone (ICC = 0.95). At this stage, using a smartphone  
268 independent of additional equipment does not offer an effective alternative for examining scoliosis.

269

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

282

283 Accelerometer-based apps may provide an effective alternative to a conventional long-arm goniometer. These  
284 apps utilise the triaxial accelerometer hardware built into smartphones, traditionally serving as position sensors  
285 for the use in video games by measuring inclination of the smartphone device (82). Ockendon and Gilbert (82)  
286 have demonstrated high reliability ( $r = 0.947$ ) and validity of a smartphone accelerometer-based app (iPhone  
287 3GS). Furthermore, the authors also found greater inter-rater reliability compared to a traditional goniometer.  
288 Given that most practitioners that typically assess range of motion (e.g. physiotherapists, strength and conditioning  
289 coaches) would do so independently, it can be argued that inter-rater reliability is not relevant to this context.  
290 However the same study did demonstrate superior intra-rater reliability compared to the traditional method,  
291 offering support for accelerometer-based apps as a viable alternative to traditional methods of goniometry. Milani  
292 *et al.* (69) argue that accelerometer-based, photographic-based, and magnetometer-based apps all possess the same  
293 limitation in that they can only measure range of motion in static conditions. Therefore for smartphone

294 applications to be considered as an effective alternative, they must be able to validly and reliably measure angular  
295 movement in dynamic conditions e.g. active rotations. More recently Bittel *et al.* (9) used the accelerometer of an  
296 iPhone 4 to measure extension and flexion movements concurrently with an isokinetic dynamometer at a range of  
297 different speeds (30, 60, 90, 120, and 150°/s). The authors demonstrated limits of agreement of 2° between the  
298 smartphone and the dynamometer.

299

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

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

<i>At current, what physiological and anatomical measurements can apps take?</i>	Commercially available apps using contact and contactless PPG technology can accurately measure resting heart rate within $\pm 4$ bpm. 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.
<i>What measurements can apps currently not take?</i>	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.
<i>Do the currently available apps offer anything beyond traditional measurements?</i>	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.

317

318 **Capacity for apps to analyse physical performance**

319

320 One of the main problems that strength and conditioning coaches face is how to objectively quantify the physical  
 321 capabilities of their athletes (37, 57). Measuring physical performance is, indeed, a key part of any training  
 322 program since it allows the practitioner to monitor and adjust workloads (44, 76), analyse fatigue (47, 106), detect  
 323 talents (38, 72), identify weaknesses (97), or prevent injuries (16, 67, 68). Thus, a common practice when  
 324 designing strength and conditioning programs is to measure specific variables of interest that could help in the  
 325 prescription of the training stimulus (42, 44, 57, 76); however, the technology and expertise required to do so is  
 326 often expensive and non-user-friendly, especially for coaches or teams outside big organizations or Universities.  
 327 For this, the rise of smartphones, which currently include several sensors specifically designed to measure physical  
 328 performance (like heart rate monitors, GPS or accelerometers) are gaining popularity in the fitness and health  
 329 community (4, 11, 107). For example, fitness and health apps are among the top fitness trends in the list elaborated

330 by the American College of Sports Medicine (107). However, just a few of the thousands of fitness apps available  
331 are scientifically validated (11). Thus, the purpose of this section is to provide an updated review of some of the  
332 most relevant studies that have analyzed the validity and reliability of smartphone apps for the measurement of  
333 several variables related to physical performance.

334

### 335 **Maximal strength**

336

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

342

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

352

353 Trying to address this limitation, an iOS app named '*PowerLift*' has been recently validated for the measurement  
354 of barbell velocity in the bench press exercise in resistance trained males (5). To do this, authors measured several  
355 repetitions in a group of powerlifters with a linear transducer (working at 1kHz) and the '*PowerLift*' app on an  
356 iPhone 6 (iOS 9.3.2) simultaneously, and then compared the results. '*PowerLift*', which consists of the recording

357 and ulterior analysis of a slow-motion video of the lift thanks to the high-speed camera on the most recent iOS  
358 devices, was significantly correlated with the linear transducer ( $r = 0.94$ ) and showed a small standard error of  
359 estimate ( $SEE = 0.008\text{m/s}$ ) in the measurement of barbell velocity. Moreover, there were no significant differences  
360 between the 1-RM predicted by the velocity measured with the linear transducer or the app, meaning that  
361 '*PowerLift*' could be a less expensive, yet accurate and valid alternative for the estimation of maximal strength.

362

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

364

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

381

382

383



384 **Human locomotion: Running and sprinting**

385

386 The analysis of human locomotion is of great interest for both performance and injury prevention purposes (68,  
387 74, 80, 96). For example, several mechanical variables such as ground contact time, leg stiffness, or the horizontal  
388 force applied to the ground has been shown to be related with running and maximal sprinting performance (73,  
389 93, 96). Moreover, studies have suggested that the asymmetries between legs in some of these variables could be  
390 used as a relevant indicator related to risk of injury (12, 50). As with the performance variables described above,  
391 the measurement of running and sprinting mechanics has usually required advanced measurement systems such  
392 as instrumented treadmills, force platforms, timing gates or radar guns (15, 75, 94); expensive technology which  
393 most coaches do not have access to. Using the same approach than with the jumping and resistance training apps  
394 mentioned above, two new apps also based on high-speed video-analysis were recently validated for the  
395 measurement of running and sprinting mechanics on an iPhone 6 (iOS 9.2.1, 240 frames per second) (3, 94). The  
396 first one, *'Runmatic'*, was tested against an infrared platform for the detection of contact and flight times during  
397 running at several speeds ranging 10-20km/h in male runners (3). Moreover, the app made use of some validated  
398 spring-mass model equations that allow the calculation of different mechanical variables based on contact time,  
399 flight time and simple anthropometrics (74). The app was shown to be valid and reliable for the measurement of  
400 leg stiffness, vertical oscillation of the centre of mass, maximal force applied to the ground, and stride frequency  
401 ( $r = 0.94-0.99$ , bias = 2.2-6.5%). The second one, *'My Sprint'*, was also shown to be highly valid and reliable for  
402 the measurement of 30 m sprint time and the production of horizontal force, velocity, and power in male sprinters  
403 in comparison with timing gates and a radar gun, with no significant differences between devices (94). Thus, these  
404 apps allow the practitioner to measure important variables related with running and maximal sprinting without the  
405 need of any advanced instruments.

406

407 **Distance tracking using GPS and accelerometer sensors**

408

409 When talking about running, probably the most popular variable in the sports technology industry is the distance  
410 covered using GPS signals (and, consequently, running pace) (14, 28, 48). Several wearable devices (mainly  
411 watches) have been used both in practice and research to measure running distances (13, 78), although the  
412 inclusion of GPS sensors on most smartphones in recent years has catalysed the creation of apps which take

413 advantage of that technology to track distances and running pace (24). In fact, distance trackers are among the top  
414 twenty fitness trends for 2017 (107); however, there is a lack of evidence regarding their validity and reliability.  
415 One recent study analysed the validity and reliability of an iOS app designed to measure distances during running  
416 by using the GPS included in the iPhone smartphones (8). To do this, researchers had subjects run on a 400 m  
417 track for a total of 2,400 m while wearing an iPhone in an armband, and then compared the values of distance and  
418 speed obtained by the app with the actual values. The app underestimated both distance and speed by 3-4%,  
419 meaning an absolute difference of approximately 100 m or 0.7 km/h. However, the good test-retest reliability  
420 observed (i.e. comparing values in two separate trials) and the relatively low bias between the app and the actual  
421 distance made the authors conclude that the app might be appropriate to track running in the general population,  
422 although it might be not adequate for trained athletes.

423

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

437

438

439

440

441 Table 2. Summary of apps for analysing physical performance

<i>At current, what physical performance measurements can apps take?</i>	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.
<i>What measurements can apps currently not take?</i>	Measure speed/acceleration during walking, jogging or running using GPS signal and daily steps.
<i>Do the currently available apps offer anything beyond traditional measurements?</i>	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.

442

443 **Practical applications**

444

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

458

459

460 **Conflicts of interest**

461 MADE ANONYMOUS.

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