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Sports Medicine

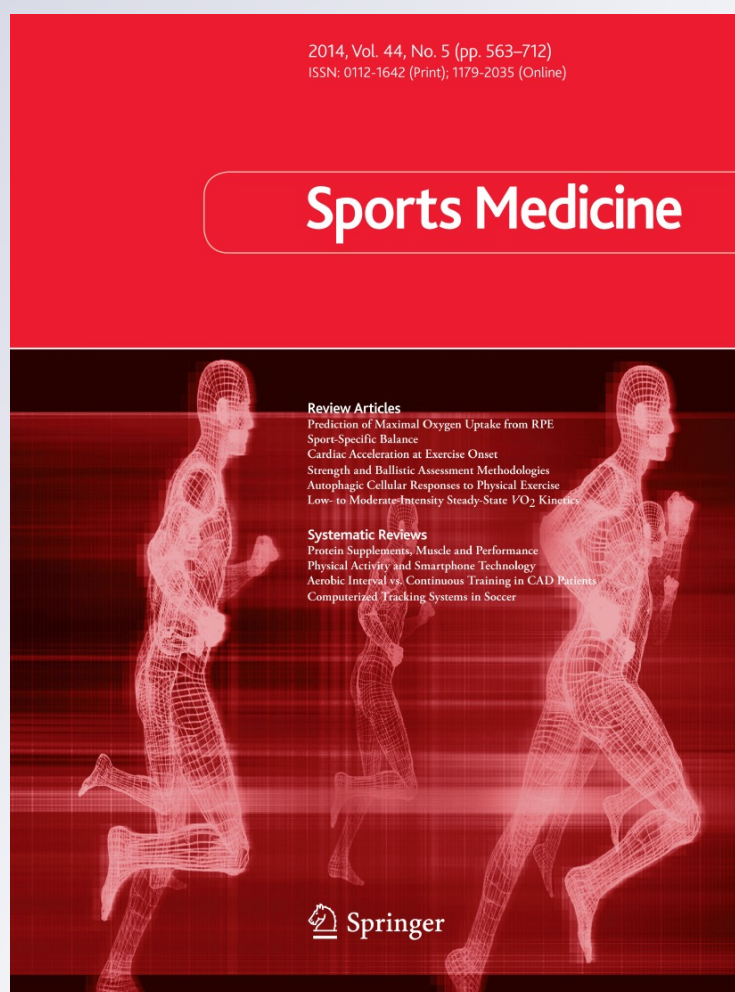
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Measuring and Influencing Physical Activity with Smartphone Technology: A Systematic Review

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Abstract

Background Rapid developments in technology have encouraged the use of smartphones in physical activity research, although little is known regarding their effectiveness as measurement and intervention tools.

Objective This study systematically reviewed evidence on smartphones and their viability for measuring and influencing physical activity.

Data Sources Research articles were identified in September 2013 by literature searches in Web of Knowledge, PubMed, PsycINFO, EBSCO, and ScienceDirect.

Study Selection The search was restricted using the terms (physical activity OR exercise OR fitness) AND (smartphone* OR mobile phone* OR cell phone*) AND (measurement OR intervention). Reviewed articles were required to be published in international academic peer-reviewed journals, or in full text from international scientific conferences, and focused on measuring physical activity through smartphone processing data and

influencing people to be more active through smartphone applications.

Study Appraisal and Synthesis Methods Two reviewers independently performed the selection of articles and examined titles and abstracts to exclude those out of scope. Data on study characteristics, technologies used to objectively measure physical activity, strategies applied to influence activity; and the main study findings were extracted and reported.

Results A total of 26 articles (with the first published in 2007) met inclusion criteria. All studies were conducted in highly economically advantaged countries; 12 articles focused on special populations (e.g. obese patients). Studies measured physical activity using native mobile features, and/or an external device linked to an application. Measurement accuracy ranged from 52 to 100 % ($n = 10$ studies). A total of 17 articles implemented and evaluated an intervention. Smartphone strategies to influence physical activity tended to be ad hoc, rather than theory-based approaches; physical activity profiles, goal setting, real-time feedback, social support networking, and online expert consultation were identified as the most useful strategies to encourage physical activity change. Only five studies assessed physical activity intervention effects; all used step counts as the outcome measure. Four studies (three pre-post and one comparative) reported physical activity increases (12–42 participants, 800–1,104 steps/day, 2 weeks–6 months), and one case-control study reported physical activity maintenance ($n = 200$ participants; >10,000 steps/day) over 3 months.

Limitations Smartphone use is a relatively new field of study in physical activity research, and consequently the evidence base is emerging.

Conclusions Few studies identified in this review considered the validity of phone-based assessment of physical

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activity. Those that did report on measurement properties found average-to-excellent levels of accuracy for different behaviors. The range of novel and engaging intervention strategies used by smartphones, and user perceptions on their usefulness and viability, highlights the potential such technology has for physical activity promotion. However, intervention effects reported in the extant literature are modest at best, and future studies need to utilize randomized controlled trial research designs, larger sample sizes, and longer study periods to better explore the physical activity measurement and intervention capabilities of smartphones.

1 Introduction

Physical activity promotion makes an invaluable contribution to the global public health agenda, through programs that target a diverse range of diseases, in different groups, settings, and countries [1]. Meta-analyses highlight the positive effects of physical activity promotion programs, but also the ongoing challenges for physical activity promoters, particularly in regard to maximizing intervention reach at the population level [2].

Technical innovations provide significant opportunities for physical activity promoters to reach populations. Internet-based interventions have the potential to encourage small, but significant physical activity changes, with a minimal outlay of time and effort [3], while the advent of smartphones allow access to Internet and applications (apps) ‘on the move’. Currently, about 6.8 billion people worldwide use mobile phones; global smartphone penetration is now 29.5 % and, in 2014, the worldwide smartphone shipments are forecast to grow 40 % to 1.0 billion units per year [4–6]. The level of connectivity and reach afforded by this technology, combined with the fact that mobile phones are often carried throughout the day, highlight the value of smartphones as a medium for measuring and influencing physical activity in real time [7].

Some reviews have evaluated the efficacy of mobile phones in general health promotion interventions, reporting that these devices can help improve health outcomes and care processes through monitoring, managing, and educating patients [2, 8, 9]. Reviews on mobile phone-based physical activity interventions are scarce and include only three studies, one of which provided evidence supporting the positive effects of interventions using the Internet, computer kiosks, and mobile phones in young people [10]. Another focused on mobile phone interventions to reduce inactivity and weight and demonstrated the beneficial impact of text messaging or apps for this purpose [11]. The third and most recent study, a meta-analysis of studies that

principally used mobile devices and text messaging to increase physical activity, highlighted the potential that mobile devices have for positively influencing physical activity behaviors [12]. However, this review did not specifically focus on smartphone technology, or, importantly, evaluate data on the application and accuracy of this technology for physical activity measurement, or user engagement.

To our knowledge, no previous study has completed a comprehensive review of the use of smartphones in physical activity measurement and promotion. Given the increasing interest in this technology within the field of physical activity, and the lack of an overview to guide future research efforts, a review of the extant literature seems timely. The aim of the present study was to undertake a systematic review of available evidence, with a specific focus on examining the extent to which smartphones can effectively be used to measure and influence physical activity.

2 Methods

2.1 Literature Search

The databases Web of Knowledge (MEDLINE and Web of Science), PubMed, PsycINFO, EBSCO (CINAHL & SPORTDiscus), ScienceDirect, and Scopus were searched for relevant articles to September 2013. We performed a keyword search using the terms physical activity OR exercise OR fitness AND smartphone* OR mobile phone* OR cell phone* AND intervention OR measurement. To attain additional eligible articles, the reference lists of the located studies were also checked.

2.2 Selection Criteria

In order to be included in the review, articles were required to be published in international academic peer-reviewed journals, or in full text from international scientific conferences (book chapters, abstracts of conference proceedings, and dissertations were excluded) and to have monitored physical activity patterns objectively either with native sensors or external sensors and/or promoted physical activity through smartphone apps. Studies only using text messages, or those that measured physical activity only through mobile phone-based questionnaires, were not included.

Two reviewers independently performed the selection of articles and examined titles and abstracts to exclude those out of scope (JBR and NG). Any disagreements on inclusions were resolved through discussions between three reviewers (JBR, NG, and ST).

2.3 Data Extraction

For selected articles, details on source (authors, year, and country), study aim, population, and study description were extracted. For articles that tested measurement accuracy, we extracted data on the technologies used to assess physical activity patterns, smartphone placement, the activity recognition algorithm, the different behaviors measured, and the accuracy of the data. For intervention articles, we extracted data on study design, technologies used to measure physical activity, behavior change strategies and, where appropriate, the theoretical framework on which the intervention was based. Primary intervention results extracted were the effect of the intervention on physical activity and health-related outcomes, participant's perceptions of intervention, and engagement and usage rates of the app.

3 Results

3.1 Study Selection

The literature searches yielded 441 unique, potentially relevant abstracts (Fig. 1). After excluding records that were out of scope, the full text of 196 records were checked. In all, 170 of these articles did not meet the inclusion criteria; main reasons were because the articles did not measure physical activity through smartphone processing data ($n = 80$; 47 %), did not aim to influence physical activity ($n = 55$; 32 %), or study outcomes were not physical activity related ($n = 28$; 17 %). Proposed smartphone physical activity studies or concept articles ($n = 4$; 2 %), and focus group studies and commercial reviews of apps on the market ($n = 3$; 2 %) were not selected for full review. This resulted in 26 articles being included in the review.

Fig. 1 Search and exclusion process. App mobile phone application

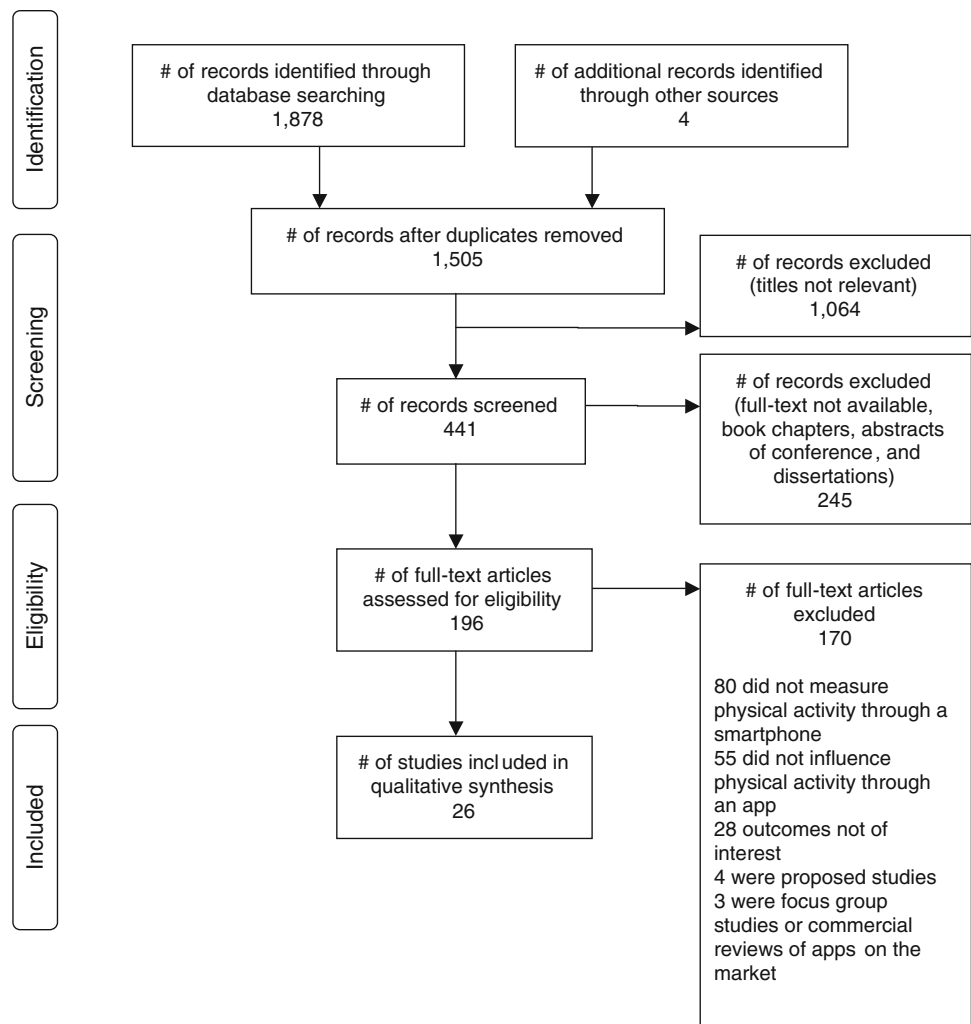


Table 1 Aims and characteristics of selected papers

Study number	Author/country	Study aim	Participants	Description
Theme 1: Papers that measured accuracy with the aim of influencing physical activity ($n = 9$)				
[17]	Donaire-Gonzalez et al. (2013) Spain	Tested accuracy of app to estimate physical activity using an in-built accelerometer	Adults $n = 36$ (23 women) Mean \pm SD 30.9 ± 7.9 years General population (different health status, age, and sex) $n = 10$	Participants wore ActiGraph GT3X accelerometer and SmPh on belt attached to waist for 5 consecutive days Two test groups (healthy, young or middle aged, and weak or old people) Two testing protocols wearing SmPh in different positions on body, on treadmills and on street roads. (1) Standing still for 10 s, walking for 20 steps, running for 20 steps; (2) Walking for 100 steps, running for 100 steps SmPh was placed inside an adjustable band attached to the chest of a participant who performed static activities (sitting, lying, standing), transitions (lie-to-sit, sit-to-lie, sit-to-stand, stand-to-sit), dynamic activities (walking self-pace, upstairs, downstairs, running, jumping), and falls (forward, right-side, backward, left-side) Participants carried SmPh in their pocket during no activity (e.g. SmPh on a table), sitting, walking, running. Each condition lasted 10 s
[22]	Gao et al. (2009) USA	Tested accuracy of app for obesity prevention using in-built accelerometer	Adults $n = 10$ (6 men) Mean \pm SD 25 ± 5 years men and 23 ± 3 years women Elderly in special care $n = 4$	Participants carried SmPh in different places (pocket, hand-held, etc.) and orientations Participants wore SmPh and external sensor while performing a 25-min protocol consisting of 5-min periods of walking and running at increasing speeds For validation, app data was compared with ECG traces, physical activity compendium of MET values and by walking 1-min periods at constant step rates (90, 120, and 150 steps/min and running at 130, 150, and 180 steps/min) Participants wore SmPh in different positions on the waist and in the pocket. First test consisted of walking 100 feet and returning. Second test consisted of a variety of outdoor conditions (lying, sitting, standing, walking, running, falling)
[16]	Yi He et al. (2013) China	Tested accuracy of in-built kinematic sensors (accelerometer, gyroscope and magnetic sensor) to recognize daily living activities	Adults $n = 10$ (6 men) Mean \pm SD 25 ± 5 years men and 23 ± 3 years women Elderly in special care $n = 4$	Participants wore SmPh and the foot sensor during the testing period. First test, one participant walked, ran and climbed stairs for 1 min and 5 min in each condition. The second and the third tests assessed two participants, in each condition, for 1 min, and also assessed transitions between conditions Protocol consisted of prescribed activities on a treadmill (1.5/3.0/4.0 mph walking and 5.5 mph jogging), and self paced activities (sitting, normal upstairs and downstairs, brisk upstairs and down stairs, 400 m slow walking, 400 m normal walking, 400 m brisk walking, 400 m jogging). Participants carried the SmPh in an armband for jogging and in the front pocket for all other activities
[13]	Ketabdar et al. (2010) Germany	Tested accuracy of app for healthcare services using in-built accelerometer	Adults $n = 20$ (10 women) Cardiac rehabilitation outpatients $n = 2$	Participants wore SmPh in different positions on the waist and in the pocket. First test consisted of walking 100 feet and returning. Second test consisted of a variety of outdoor conditions (lying, sitting, standing, walking, running, falling)
[35]	Khalil et al. (2009) UAE	Tested accuracy of app for walking recognition using an in-built accelerometer	Adults $n = 20$ (10 women) Cardiac rehabilitation outpatients $n = 2$	Participants wore SmPh and the foot sensor during the testing period. First test, one participant walked, ran and climbed stairs for 1 min and 5 min in each condition. The second and the third tests assessed two participants, in each condition, for 1 min, and also assessed transitions between conditions Protocol consisted of prescribed activities on a treadmill (1.5/3.0/4.0 mph walking and 5.5 mph jogging), and self paced activities (sitting, normal upstairs and downstairs, brisk upstairs and down stairs, 400 m slow walking, 400 m normal walking, 400 m brisk walking, 400 m jogging). Participants carried the SmPh in an armband for jogging and in the front pocket for all other activities
[29]	Mattila et al. (2009) Finland	Tested accuracy of app for home-based exercise program using an external heart rate and accelerometer sensor	Adults $n = 6$	Participants wore SmPh and the foot sensor during the testing period. First test, one participant walked, ran and climbed stairs for 1 min and 5 min in each condition. The second and the third tests assessed two participants, in each condition, for 1 min, and also assessed transitions between conditions Protocol consisted of prescribed activities on a treadmill (1.5/3.0/4.0 mph walking and 5.5 mph jogging), and self paced activities (sitting, normal upstairs and downstairs, brisk upstairs and down stairs, 400 m slow walking, 400 m normal walking, 400 m brisk walking, 400 m jogging). Participants carried the SmPh in an armband for jogging and in the front pocket for all other activities
[36]	Lee et al. (2011) South Korea	Tested accuracy of app for metabolic syndrome linked to a website, using an in-built accelerometer	Adults $n = 6$	Participants wore SmPh and the foot sensor during the testing period. First test, one participant walked, ran and climbed stairs for 1 min and 5 min in each condition. The second and the third tests assessed two participants, in each condition, for 1 min, and also assessed transitions between conditions Protocol consisted of prescribed activities on a treadmill (1.5/3.0/4.0 mph walking and 5.5 mph jogging), and self paced activities (sitting, normal upstairs and downstairs, brisk upstairs and down stairs, 400 m slow walking, 400 m normal walking, 400 m brisk walking, 400 m jogging). Participants carried the SmPh in an armband for jogging and in the front pocket for all other activities
[14]	Sheng-Zhong et al. (2010) China	Tested accuracy of accelerometer-foot sensor and app to estimate walking habits	General population (different height, age and sex) $n = 3$	Participants wore SmPh and the foot sensor during the testing period. First test, one participant walked, ran and climbed stairs for 1 min and 5 min in each condition. The second and the third tests assessed two participants, in each condition, for 1 min, and also assessed transitions between conditions Protocol consisted of prescribed activities on a treadmill (1.5/3.0/4.0 mph walking and 5.5 mph jogging), and self paced activities (sitting, normal upstairs and downstairs, brisk upstairs and down stairs, 400 m slow walking, 400 m normal walking, 400 m brisk walking, 400 m jogging). Participants carried the SmPh in an armband for jogging and in the front pocket for all other activities
[15]	Wu et al. (2012) USA	Tested the accuracy of an app using an in-built accelerometer or accelerometer and gyroscope, for classifying types of physical activities	Adults $n = 16$ 19–20 years	Participants wore SmPh and the foot sensor during the testing period. First test, one participant walked, ran and climbed stairs for 1 min and 5 min in each condition. The second and the third tests assessed two participants, in each condition, for 1 min, and also assessed transitions between conditions Protocol consisted of prescribed activities on a treadmill (1.5/3.0/4.0 mph walking and 5.5 mph jogging), and self paced activities (sitting, normal upstairs and downstairs, brisk upstairs and down stairs, 400 m slow walking, 400 m normal walking, 400 m brisk walking, 400 m jogging). Participants carried the SmPh in an armband for jogging and in the front pocket for all other activities

Table 1 continued

Study number	Author/country	Study aim	Participants	Description
Theme 2: Papers that measured accuracy and influenced physical activity throughout an intervention ($n = 1$)				
[18]	Anderson et al. (2007) UK	Tested accuracy of app using the fluctuation of mobile signal strength to estimate and promote physical activity Explored participants' perceptions and use of the app	Adults $n = 9$ (5 women) 19–54 years	<p>Three groups were asked to use the SmPh during a normal day. Group 1 ($n = 2$; inactive people), group 2 ($n = 3$; two moderately and one highly active), and group 3 ($n = 4$; one inactive, two moderately and one highly active). Participants then completed a paper physical activity diary for 3 days, were trained to use app for the next 2 days, and used the app and diary for 5 working days</p> <p>After intervention, participants completed semi-structured interviews to explore app experiences, and the system logs were analysed for usage rate. Physical activity accuracy was tested for 3 sample days, for two different participants, and was compared with the paper diaries and the interviews</p>
Theme 3: Papers that intervened, but did not test the accuracy of physical activity measurement ($n = 16$)				
[19]	Arsand et al. (2010) Norway	Assessed intervention effects and participants' perceptions/usage of an app and external sensor, to self-manage diabetes	Type 2 diabetes $n = 12$ (8 women) Mean \pm SD 56.2 \pm 9.6 years	<p>Pre-post study: app, pedometer, and blood glucose sensor were used by participants for 2–3 months. Focus groups and questionnaires explored users' perceptions, and pre-post physical activity assessment assessed intervention impact. Engagement was evaluated based on frequency of app use</p>
[23]	Fukuoka et al. (2010) USA	Assessed intervention effects of a pedometer and app-based diary intervention on sedentary lifestyle	Women $n = 42$ Mean \pm SD 48 \pm 13 years	<p>Pre-post study: participants used a pedometer and app; at baseline (1 week) they received educational information about physical activity benefits and entered daily step counts and physical activity frequency, intensity, and duration into an app diary</p> <p>During intervention (2 weeks), physical activity monitoring continued and daily prompts were delivered by the app, encouraging a 20 % weekly increase in steps</p> <p>Baseline and intervention assessment also included survey assessed health status, self-efficacy, physical activity barriers, and social support for physical activity, along with directly measured weight and height to calculate BMI</p>
[24]	Fukuoka et al. (2011) USA	Assessed use of a pedometer and app-based physical activity diary based in a sedentary lifestyle intervention	Same as Fukuoka et al. (2010) [23]	<p>Protocol the same as Fukuoka et al. (2010) [23], but pedometer and app compliance was assessed with data entry divided by 21 days. Bland Altman plots were used to evaluate the level of agreement between daily steps entered into the app and pedometer step counts</p>
[38]	Fukuoka et al. (2012) USA	Explored perceptions of pedometer and app based diary use in a sedentary lifestyle intervention	Same as Fukuoka et al. (2010) [23]	<p>Qualitative study post intervention: protocol the same as Fukuoka et al. (2010) [23], but participants were involved in post-intervention, semi-structured interviews to examine app acceptability and understanding motivators and barriers to increase physical activity</p>

Table 1 continued

Study number	Author/country	Study aim	Participants	Description
[37]	Kirwan et al. (2012) Australia	Assessed the intervention effects, perceptions, and use of a self-monitoring app to improve health behaviors	Adults Total $n = 200$ $n = 50$ (26 men) Mean \pm SD 39.3 ± 12.8 years $n = 150$ (88 men); Mean \pm SD 41.1 ± 12.1 years	Case-control study: all participants were existing members of the 10,000 Steps program. The intervention group ($n = 50$) used an app and/or website to log step counts for 3 months. Control group participants ($n = 150$) were existing 10,000 Steps program users. Step counts were reported with a pedometer 3 months pre-intervention and 3 months during the intervention. Usability and usefulness questionnaires were completed post-intervention; engagement was evaluated using frequency of app use
[32]	Lee et al. (2010) South Korea	Assessed intervention effects, perceptions, and use of an app for weight management	Obese adults Total $n = 36$ $n = 19$ Mean 29.5 years Mean 29.5 years	Pre-post study with a control group: participants were assigned to an intervention ($n = 19$) and control group ($n = 17$). The intervention group used the app for 6 weeks, which consisted of a game and exercise plan. Surveys assessed satisfaction at the end of the study and body composition measures (fat mass, weight, and BMI) were undertaken pre-post intervention. Engagement was evaluated using frequency of app use
[30]	Mattila et al. (2008) Finland	Assessed intervention effects, perceptions, and use of an app and pedometer, for weight and wellness management	Overweight or obese adults/psychological rehabilitation patients Total $n = 46$ $n = 29$ (20 men) Mean \pm SD 39.4 ± 8.1 years $n = 17$ (14 women) Mean \pm SD 54.5 ± 5.4 years	Pre-post study: study began with educational session about weight management. Participants were then given a pedometer and installed a diary app on their SnnPh. Group 1 ($n = 29$; obese or overweight participants) entered drink and food intake, exercise levels, steps, and weight into the app for 12 weeks; group 2 ($n = 17$; psychological rehabilitation participants), entered blood pressure, weight, steps, exercise levels, sleep and stress levels, and sent these data to the researchers once a week Pre-post weight changes were assessed; use issues were explored through a post-intervention questionnaire and semi-structured interviews; engagement was evaluated using frequency of app use
[31]	Mattila et al. (2010) Finland	Assessed the intervention effects of an app and pedometer on weight management	Obese or overweight adults $n = 27$ (20 men) 25–54 years	Pre-post study: protocol the same as Mattila et al. (2008) [30], but with one group enrolled in 12-week intervention
[25]	Nguyen et al. (2009) USA	Assessed intervention effects, perceptions, and use of an app and pedometer on a pulmonary rehabilitation program	Patients with COPD Total $n = 17$ $n = 8$ (5 women) Mean \pm SD 64 ± 12 years $n = 9$ (6 women) Mean \pm SD 72 ± 9 years	Pre-post study with a comparison group: all participants received an exercise program (that they were likely to sustain over time), and then were randomized into two arms: a mobile-coached group ($n = 9$), who monitored physical activity and COPD symptoms with feedback; and a mobile self-monitored group ($n = 8$) who monitored physical activity and COPD symptoms alone Baseline, 3-, and 6-month assessment for physical activity and cycling performance tests. Acceptability was assessed through interviews and engagement using frequency of app use at the same time points

Table 1 continued

Study number	Author/country	Study aim	Participants	Description
[27]	Schiel et al. (2010) Germany	Assessed the intervention effects of an external motion sensor and in-built accelerometer on weight reduction	Overweight or obese adolescents $n = 30$ Mean \pm SD 14 \pm 3 years	Pre-post study: participants undertook a weight-reduction teaching program (mean duration 35 days) and used an external motion sensor, in-built SmPh accelerometer and paper-diary to monitor physical activity Baseline and intervention measurements were taken for body weight, BMI, and body fat mass, and a standardized questionnaire administered to assess wellbeing, QOL, self-efficacy, social support, and motivation Protocol the same as Schiel et al. (2010) [27]
[28]	Schiel et al. (2011) Germany	Assessed intervention effects and participant perceptions of an external motion sensor and in-built accelerometer on weight reduction	Overweight or obese adolescents $n = 124$ (56 girls) Mean \pm SD 13.5 \pm 2.8 years	
[33]	Stuckey et al. (2011) Canada	Assessed intervention effects of self-monitoring blood glucose, BP, physical activity, and weight to positively impact CVD risk factors	Metabolic syndrome patients $n = 24$ (18 women) Mean \pm SD 56.5 \pm 8.9 years	Pre-post study: participants were provided with a SmPh, a BP monitor, a glucometer, pedometer, and educational information. The intervention that followed used a 2-month data plan based on physical activity and lifestyle modifications. The app allowed participants to interface with experts and self-monitor personal health indicators At week 0, 4, and 8 participants completed physical examinations (height, weight, waist circumference, BP, and heart rate), as well as blood and step tests
[26]	Toscos et al. (2008) USA	Explored perceptions of an app/pedometer based intervention, to support physical activity change	Adolescents (girls) $n = 8$ Mean 13 years	Pre-post study: three groups of friends wore a pedometer at baseline for a week and recorded the step counts using a paper diary. Step counts were entered into an app several times each day, for the next 2 weeks. Semi-structured interviews were conducted at the end of the 3rd week
[21]	Tsai et al. (2007) USA	Explored perceptions and use of an app that self-monitored energy balance	Overweight or obese adults Total $n = 15$ (9 women) 18–51 years $n = 5$ (each group)	Post-test study with a comparative group: participants were randomized into a comparative group (paper diary) and two intervention groups, one of which received one daily activity/diet prompt, and the other received two prompts through an app, over a month Perceptions of satisfaction and usability were evaluated by a post-test questionnaire and use through data entry
[20]	van Dantzig et al. (2012) Netherlands	Explored perceptions of the app using an in-built accelerometer, which aimed to persuade office workers to take regular breaks from sitting	Office workers $n = 8$ (4 women)	Qualitative study post-intervention: participants were invited to use the app for 1 working day and then interviewed about usability and acceptance
[34]	Varnfield et al. (2011) Australia	Explored perceptions and use of a home care intervention app and website	Cardiac rehabilitation patients $n = 15$ Mean 59 years	Post-test study: participants were given a SmPh with an integrated accelerometer sensor/diary app, and a BP sensor and scale. They were asked to enter health information (weight, fat percentage, food and drink intake, exercise, stress, BP, and sleep time) over 6 weeks Usability and acceptance were assessed at the end of the intervention by a questionnaire. Adherence was determined through analysis of uploaded data during the intervention

App mobile phone application, BMI body mass index, BP blood pressure, COPD chronic obstructive pulmonary disease, CVD cardiovascular disease, ECG electrocardiogram, MET metabolic equivalent, QOL quality of life, SD standard deviation, SmPh smartphone

3.2 Paper Characteristics

Selected articles emerged into three main categories: articles that tested measurement accuracy, with the aim of influencing physical activity in subsequent studies ($n = 9$) [13–17], those that concurrently tested measurement accuracy and influenced physical activity through intervention ($n = 1$) [18], and those that intervened, but did not test measurement accuracy ($n = 16$) [19, 20].

Table 1 describes the aims and characteristics of selected papers relative to these categories, with the first two articles published in 2007 [18, 21], and the highest number of articles (seven) published in 2010. A variety of countries were represented, with the majority of studies originating from the USA [15, 21–26], Germany [13, 27, 28], and Finland [29–31].

Twelve articles focused on chronic diseases and rehabilitation programs in overweight and obese adolescents [27, 28] or adults [21, 31, 32]; chronic obstructive pulmonary disease [25], metabolic syndrome [33], diabetes [19], cardiac [29, 34], or psychological rehabilitation [30] patients; and the elderly in special care [13]. Fourteen articles focused on non-clinical samples in the general population [14, 22], or adolescents [26], adults [15–18, 35–37], and women [23, 24]. One article developed a smartphone application to reduce sitting time in office workers [20].

3.3 Measuring Physical Activity

Tables 2 and 3 highlight the different types of smartphone measurement technologies used. In addition to objectively monitoring physical activity, several studies added self-report data concerning activity context, other health-related behaviors, or activities not able to be recorded by the measurement sensor (e.g. water activities) using an app diary [19, 21, 33, 34, 37].

Regarding objective measurement, we found studies that used either an external device (where data were transferred automatically via Bluetooth connection) or entered manually by the user into the smartphone app, processing data; other studies used the native features of the smartphone to measure and process the data. Eleven studies used an external measurement device such as a pedometer [19, 21, 25, 26, 30, 33, 37], an accelerometer-based motion sensor [14], or an external multi-sensor device that included an accelerometer and heart rate sensor [29].

Twelve studies monitored physical activity using native smartphone features; most of these studies used an accelerometer housed in the phone [13, 17, 20, 34–36]. Other technologies included a digital watch control estimating energy expenditure from activity duration [32], monitoring of the fluctuation of the phone's signal strength [18], or a

combination of different kinematic sensors (accelerometer, gyroscope [15, 16], and magnetic sensor) [16]. One study measured physical activity with an external device and the smartphone's in-built accelerometer [27, 28].

3.3.1 Measurement Accuracy

Ten studies described the accuracy of the physical activity data measured by the smartphone [13, 15–18]; the key findings from these studies are summarized in Table 2. Phone or external sensor position for physical activity recognition varied across studies, and included placement in the waist-hip area (pocket or clipped to a belt) [13, 15, 17, 35, 36], on the chest, in a bag, held in the hand [16, 22, 29], on an armband [15], or placed on the foot [14]; one study did not specify a position and assessed accuracy during normal smartphone use [18]. Physical activity was measured using a variety of supervised and non-supervised machine learning algorithms, using tri-axial acceleration data from the phone's native sensor [13, 15–17, 35, 36] or an external accelerometer device [14, 29]. Algorithms were trained to recognize a range of activities (walking, running, climbing stairs) and postures (standing, sitting, lying), as well as transitions between different behaviors and/or postures. Overall, studies reported measurement accuracy ranging from 52 to 100 %.

3.4 Influencing Physical Activity

Table 3 summarizes the results of intervention studies, including the strategies used, underpinning theoretical frameworks, major findings, and participant perspectives and engagement.

3.4.1 Behavior Change Theories and Intervention Strategies

Five interventions were based on behavior change theories, including social cognitive theory [18, 25, 30, 33], and the trans-theoretical model [18]. However, a range of interactive strategies and approaches were used to encourage physical activity change. Several interventions were implemented only through the smartphone [19–21, 24, 27, 28, 31, 32], whereas other interventions connected the app to a website [18, 25, 33, 34, 37]. Web technology served three purposes: as a support platform to provide individual feedback and health-related information [18, 33, 34]; as a social support network to share physical activity levels achieved during the intervention, as well as intervention experiences between friends [18, 26]; and for health professionals, especially in clinical diseases or rehabilitation programs, to check the progress of users [25, 33, 34].

Table 2 Summary of papers reporting the accuracy of smartphone physical activity measurement

Study number	Author/country	Measurement technology	Position	Algorithm	Behaviors measured	Key findings (% accuracy)
[18]	Anderson et al. (2007), UK	App used patterns of fluctuation in mobile signal strength and number of cell phone tower locations	Normal	SmPh use ANN HMM	Stationary, walking, or travelling (car, bus, or train)	ANN: stationary (83 %), walking (87 %), and travelling (73 %) HMM: stationary (92 %), walking (80 %), and travelling (74 %)
[17]	Donaire-Gonzalez et al., (2013), Spain	In-built accelerometer	On a belt attached to the waist	Freedson's MET prediction algorithm Phone-based vertical axis g-force converted to ActiGraph counts/min via linear regression	Time spent in sedentary, light, moderate, and vigorous physical activity, and energy expenditure (METs) vs. estimates from the ActiGraph GT3X	Mean difference between ActiGraph GT3X and the app was 2.24 % (95 % CI 0.76–3.72) for the duration of active time (>1.5 METs) and 0.07 METs (95 % CI 0.04–0.1) for physical activity intensity Measures of vigorous physical activity showed a tendency to underestimate the duration in vigorous physical activity
[22]	Gao et al., (2009), USA	In-built accelerometer	SmPh on the chest, waist at the front, and at the side of the hip, upper pocket	ANN on raw tri-axial accelerometer signal with band pass filtering	Walking or running	Held still in front of the chest when walking (100 %) and running (100 %) Front waist walking (98–100 %) and running (98 %); side waist walking (96–100 %) and running (94–97 %) Upper pocket while walking (100–105 %) and running (97–98 %)
[16]	Yi He et al. (2013) China	In-built accelerometer, gyroscope, and magnetic field sensor	Placed inside an adjustable band attached to the chest	A binary hierarchical classifier system was used to recognize 14 activities	Static activities (sitting, lying, standing), transitions, dynamic activities (walking, upstairs, downstairs, running, jumping), and falls	Static activities (98 %), transitions (94 %), dynamic activities (91 %)
[13]	Ketabdar et al. (2010), Germany	In-built accelerometer	Trouser pocket	Gaussian Mixture Model	Stationary, walking, or running	Stationary (96 %), walking (93 %), and running (93 %)
[35]	Khalil et al., (2009), UAE	In-built accelerometer	Upper pocket, lower pocket and side pocket, hand-held, bag	Dynamic Peak Detection Algorithm	Walking	Upper pocket (88–99 %), lower pocket 86 %, side pocket (84–92 %), hand-held (97–100 %), and bag (92–100 %)
[29]	Mattila et al. (2009), Finland	External accelerometer and heart rate monitor with input uploaded to the app via Bluetooth	Integrated accelerometer and electrode unit worn on chest	Peak Detection Algorithm after Fast Fourier Transformation of acceleration signal Regression-based prediction of energy expenditure	Walking Energy expenditure	Step rate detection was very accurate at step rate of 90 steps per minute or more Energy expenditure (METs) estimation was fairly accurate at walking speeds (0.996, $p < 0.01$), unreliable results when running

Table 2 continued

Study number	Author/country	Measurement technology	Position	Algorithm	Behaviors measured	Key findings (% accuracy)
[36]	Lee et al., (2011), South Korea	In-built accelerometer	Waist, trouser pocket	Fuzzy C means clustering algorithm	Lying, sitting, standing, walking, running, or falling	Lying (100 %), sitting (96 %), standing (98 %), walking (98 %), running (100 %), and falling (99 %) Overall activity classification (98 %), waist (99.6 %) and trouser pocket (99.1 %)
[14]	Sheng-Zhong et al., (2010), China	External accelerometer with input uploaded to the app via Bluetooth	Foot	Dynamic Peak Detection Algorithm	Walking, running, climbing stairs, or gait transitions	Walking (100 %), running (96 %), up-stairs (98 %), and gait transitions (95 %)
[15]	Wu et al. (2012), USA	In-built accelerometer and gyroscope	Front shorts pocket, armband	Multiple algorithms evaluated. Decision tree, ANN, naïve Bayes, logistic regression, kNN	Walking, climbing up and down stairs, jogging, sitting	The kNN classifier achieved high accuracies for walking at different paces (90–94 %), jogging (91 %), and sitting (100 %). Activity recognition was lowest for climbing stairs (52–79 %)

ANN artificial neural network, App mobile phone application, CI confidence interval, HMM hidden Markov model, kNN k-nearest neighbor, METs metabolic equivalents, UAE United Arab Emirates

User profiles and real-time feedback were used in six studies [18, 20, 27, 28, 32, 34] through a visual icon on the screen to denote accumulated time spent in certain activities [18, 20, 27, 28]. Other studies provided a summary of activities at the end of the day; five studies displayed graphical feedback of the user's daily physical activity profile, energy balance, or other health-related variables [21, 31–34]. The majority of apps also provided an historical view showing progress across previous weeks, through visual graphs or a calendar day [18, 25, 34].

A number of apps delivered automatic, motivational text messages to facilitate contact between users and health professionals [30, 31]; sent motivational text messages from health professionals [34]; or used text messaging as a means to network and share experiences, information, and achievements among friends [18, 26]. Other interactive strategies included using games as a tool to learn about balance [32], and tips and suggestions on how to be physically active and overcome common barriers to change [25].

3.4.2 Intervention Effects

From 17 articles that implemented and evaluated a smart-phone-based intervention, ten studies quantified health-related [32, 33] and/or physical activity effects [19, 23, 25, 33, 37]. Seven of these studies reported on weight-related outcomes and other cardiovascular disease risk factors, as well as quality of life. Overall sample size ranged from 17 to 124 participants, with interventions lasting from 1 week to 6 months. Five studies used single group pre–post designs [27, 30, 31, 33] and only two studies used pre–post designs relative to a control [32] or comparison [25] group. Of these, four studies reported statistically significant improvements in weight and body fat reduction [27, 32, 33], blood pressure, and cholesterol [33].

Five intervention studies reported physical activity effects [19, 23, 25, 33, 37] using step counts, with sample sizes ranging from 12 to 200 participants, over a study duration of 2 weeks to 6 months. Three studies using single group pre–post study designs [19, 23, 33] identified positive intervention effects, with mean physical activity increases ranging from 800 to 1,104 steps/day. Nguyen et al. [25] compared two groups using different apps within a 6-month pre–post study; participants in one group ($n = 8$) only applied the monitoring system of an app, while those in the other group ($n = 9$) used both monitoring and influencing strategies. The study findings showed small but significant increases in the monitoring-only group (mean of +609 daily steps; $p = 0.04$), whereas step counts decreased in the monitoring and influencing group (mean of –1,017 daily steps; $p = 0.04$); the researchers attributed these results to differences in baseline characteristics and the small sample size.

Table 3 Summary of intervention papers

Study number	Author/country	Technologies	Strategies	Theoretical framework	Key findings (1 = physical activity/health effects, 2 = participant perceptions, 3 = engagement)
[18]	Anderson et al., (2007), UK	App used patterns of fluctuation in mobile signal strength to measure activities	App provided real-time feedback (every 30 s) when stationary, moderately active (walking) and when travelling in a car, bus, or train Users could compare their own and others activities across the previous week; data were uploaded (every hour) to the website; contacts could be specified and changed	Trans-theoretical model, social cognitive theory	1. Not reported 2. App was perceived as easy and fun to use, and increased awareness of physical activity levels. Participants enjoyed competing among themselves; social support through sharing activity experiences and strategies (e.g. walk while working) was highlighted as particularly effective 3. Use ranged from 1 and 34 times a day, with engagement higher in the evening
[19]	Arsand et al., (2010), Norway	External pedometer measured step counts with input uploaded to the SmPh via Bluetooth Participants could also enter step counts and nutrition habits	App provided tips, short messages, and feedback on progress; participants were able to view and change goals related to food habits and step counts	Not reported	1. Mean counts increased from 5,355 steps/day at baseline to 6,459 daily steps in the last week of the 2–3 month intervention (mean increase of 1,104 steps/day; $n = 12$) 2. Participants were motivated by challenges, and being able to visualize step count goals 3. Physical activity progress checked once per day and other functions accessed on average 1.7 times a week
[23, 24, 38]	Fukuoka et al., (2010–12), USA	External pedometer with step counts entered into the app	App set weekly goals based on steps, and participants asked to increase counts by 20 % from the previous week Daily messaging and prompts regarding benefits, barriers, and social support for increasing physical activity	Not reported	1. Mean increase of 800 steps/day ($p < 0.001$) over a 2-week intervention ($n = 42$) 2. Participants reported that (a) the combination of an app diary and pedometer acted as a powerful self-monitoring tool; (b) feedback and daily messages motivated physical activity; (c) goal settings allowed the development of personal physical activity strategies 3. 94 % of the sample used the pedometer and 88 % used the app diary
[37]	Kirwan et al., (2012), Australia	External pedometer with counts entered into the app Activity type and duration of physical activity also entered	App provided feedback on physical activity and synchronized with a website. Step counts could be compared across previous weeks	Not reported	1. Intervention group ($n = 50$) maintained walking above mean of 10,000 daily steps. Non-app comparison group ($n = 150$) reduced walking by mean of 4,000 daily steps over 3-month intervention ($p < 0.001$) 2. 80 % of participants reported either agreeing or strongly agreeing on app usefulness. Ratings on usability and usefulness of the app were high 3. Website intervention use declined in the control group (41 days) vs. intervention group (62 days). App use was associated with an increased likelihood of logging daily steps during the intervention period vs. those not using the app (OR 3.56, 95 % CI) and with an increased likelihood of logging >10,000 steps on each entry (OR 20.64, 95 % CI)

Table 3 continued

Study number	Author/country	Technologies	Strategies	Theoretical framework	Key findings (1 = physical activity/health effects, 2 = participant perceptions, 3 = engagement)
[32]	Lee et al., (2010), South Korea	Digital watch control estimating energy expenditure from activity duration Supplemental information entered manually to estimate the caloric balance	App provided feedback on calories consumed and energy expended with caloric balance displayed for the present, previous week, and previous month Based on this information, a three-dimensional image representing the user's weight changes (skinny, normal, and fat) was displayed A quiz game provided educational information about how to control caloric balance	Not reported	1. Body composition measures (fat mass, weight, BMI) significantly decreased ($p < 0.05$) for the intervention group ($n = 17$), but did not significantly decrease in the comparison group ($n = 19$), for 6 months 2. 58 % of the intervention group agreed that the app was easy to use and that the contents were interesting. All participants agreed that the system was easy to access 3. 75 % used the system once a week and 8 % used it every day; 58 % intended to use it in the future and 67 % stated that they would recommend it
[30, 31]	Mattila et al., (2008–10), Finland	External pedometer with counts entered into the app, or wireless uploaded Supplemental data included food and drink, weight, BP, sleep, stress, and feelings states	App provided graphical feedback based on wellness variables Historical entries were shown on a calendar day view Personal information sent from the app to an expert via multimedia messages or e-mail	Cognitive behavioral therapy	1. Among participants who reduced weight (mean -2.94 kg; $p < 0.01$) and those who did not (mean $+0.193$ kg), the physical activity duration after 12-week intervention was 132 min vs. 65 min, respectively 2. Participants reported that the app was easy to use (76–93 %), and it motivated them to be more active (86–71 %); 79 % said that the application helped them in weight management; 76 % found the feedback graphs useful 3. The average number of entries made per day was 5.32 (range = 0–14). Participants who lost weight made more entries to the app
[25]	Nguyen et al., (2009), USA	External pedometer with counts entered into the app Supplemental data included exercise type, duration, and intensity	The app displayed feedback based on data entered daily; historical entries summarizing exercise completed over the week Data transmitted in real-time to a web server for expert checking Participants received reminders to complete entries by an auditory signal; if unable to exercise, they were asked to select reasons from a list of common barriers	Behavioral theories	1. Over 6 months, the mobile self-monitored group ($n = 9$) increased physical activity mean by 609 steps/day ($p = 0.04$), whereas physical activity in the mobile coach group ($n = 8$) declined (mean 1,017 steps/day; $p = 0.04$). There were no group differences in cycle performance or 6-mile walk time 2. Participants reported that logging exercise and symptoms was easy and that keeping track of exercise helped them remain active; text messaging was not perceived favorably 3. Participants who received feedback in the self-monitored group submitted more data than those in the mobile coach group (87 % vs. 66 % over 6 months)
[27, 28]	Schiell et al., (2010–11), Germany	External device and in-built accelerometer Supplemental data included caloric intake assessed by a camera in the SmPh	App displayed real-time physical activity feedback (duration and intensity) and time to reach set goals	Not reported	1. Over an average duration of 35 days, participants significantly reduced weight, BMI, total body fat mass, and % body fat post-intervention ($p < 0.01$). Physical activity duration was associated with weight reduction ($p < 0.05$) 2. The app. was highly accepted by children and adolescents who were overweight or obese 3. Not reported

Table 3 continued

Study number	Author/country	Technologies	Strategies	Theoretical framework	Key findings (1 = physical activity/health effects, 2 = participant perceptions, 3 = engagement)
[33]	Stuckey et al., (2011), Canada	External pedometer with counts entered into the app. Supplemental data included BP, heart rate, blood glucose, and weight	The app provided graphical feedback based on step counts, BP, heart rate, blood glucose, and weight, with data transmitted to a web server Predetermined thresholds for metabolic syndrome and CVD risk were programmed into the web server, with an email sent to an expert when data exceeded thresholds The app reported daily step counts and transmitted data to the other members of the group and a website Participants were able to send text messages to each other to encourage walking, and these messages were logged on a website and published daily Progress relative to step goals was also published on this website	Self-efficacy, decisional balance and stage of change	1. Participants ($n = 24$) increased physical activity mean by 1,086 daily steps over 2 months ($p = 0.003$); training heart rate and aerobic capacity increased ($p < 0.001$); BMI ($p = 0.03$), waist circumference ($p = 0.002$), diastolic BP ($p = 0.046$), and total cholesterol ($p = 0.009$) all reduced 2. Not reported 3. Not reported
[26]	Toscos et al., (2008), USA	External pedometer with counts entered into the app	The app reported daily step counts and transmitted data to the other members of the group and a website Participants were able to send text messages to each other to encourage walking, and these messages were logged on a website and published daily Progress relative to step goals was also published on this website	Not reported	1. Not reported 2. Social support and sharing step counts encouraged behavior change behaviors but competition element was perceived negatively by adolescent girls. Motivational messages between friends were not effective, while small groups of close friends were preferred over large groups 3. Not reported
[21]	Tsai et al., (2007), USA	External pedometer with counts entered into the app Supplemental data included food and drink intake, location, and physical activity type	App displayed positive or negative energy balance at the end of each day; previous days' data could be viewed Feedback on goals was also displayed and reminders to enter caloric data sent to the participants	Not reported	1. Not reported 2. Self-monitoring increased awareness. The application was convenient and easy to use, but participants reported that prompts were disruptive 3. App diary was used 87–99 % of the time vs. 59–61 % for the paper diary
[20]	Van Dantzig et al., (2012), Netherlands	In-built accelerometer	App displayed real-time physical activity feedback with a visual icon showing current and accumulative minutes/day, which could be shared with friends Tailored reminders given to break from sedentary behavior (visual, acoustic, and tactile signals), by default for 5 min each 60-min bout	Not reported	1. Not reported 2. 6/8 participants were generally positive about their interaction with the app; 5/8 reported development of new skills and knowledge to break sitting time. Scores on attractiveness were predominantly low (5/8) Participants appreciated the vibration signal to break from sitting, whereas the auditory signal was distracting. Some participants reported battery problems, with the app consuming too much power. Carrying the SmpH continuously was problematic for some users 3. Not reported
[34]	Vamfield et al., (2011), Australia	In-built accelerometer Supplemental data included weight, food intake, sleep, stress, alcohol intake, smoking, exercise, and BP	App provided feedback on step counts, distance, energy expenditure and physical activity duration, in real-time, and a physical activity summary for the day, week, and month Data were transmitted to a web server for expert review on progress, feedback, and goal setting through weekly telephone mentoring sessions and motivational messages	Not reported	1. Not reported 2. Features were practical, easy to use and motivated participants to reach their goals; 91 % reported that expert consultation was particularly effective 3. The app diary was used extensively (91.5 %); when automated step logging was included, average usage rate increased to 97 %. The website was not used regularly (36 %)

App mobile phone application, BMI body mass index, BP blood pressure, CI confidence interval, CVD cardiovascular disease, OR odds ratio, SmpH smartphone

One study [37] used a case-control study design to evaluate the effectiveness of a web-based intervention that used an app to log daily steps. Participants who used the app and the website were able to maintain mean levels of physical activity above 10,000 daily steps, while existing participants of the website program who did not access the app significantly reduced their physical activity levels by a mean of 4,000 steps/day after 3 months of membership ($p < 0.001$).

3.4.3 Participant Perspectives and Engagement

Twelve studies used either a quantitative or a qualitative approach to assess participant perspectives and usability of the smartphone. Users highlighted monitoring their physical activity profile [21, 38], real-time feedback [19, 25, 30, 38], social networking [18, 26], expert consultation support [34], and goal setting as key features that facilitated physical activity engagement [19, 38], as well as the usability of the app [18–20, 25, 28, 30, 34, 37]. A number of studies highlighted other features that tended to limit engagement, such as disruptive issues with the use of prompts and auditory signals [21] and text messaging that was perceived unfavorably among older age participants [25]. In one study, competition-based strategies were perceived negatively among adolescent girls [26].

Nine studies evaluated compliance, with frequency of use ranging from two times a week to 34 times a day [18, 19, 30, 32]. Two studies showed considerably higher usage rates when the app was combined with an external pedometer [24], or an in-built accelerometer [34]. Another study reported a higher usage rate for an app-based dietary and physical activity diary (87.1–99.1 %) compared with a paper dietary and physical activity diary (59.3–60.7 %) [21]. In the *10,000 Steps* study [37], app use was associated with an increased likelihood of logging daily steps during intervention, compared with website use alone, and with an increased likelihood of logging more than 10,000 steps on each entry. Finally, Nguyen et al. [25] reported that participants who used an app solely as a self-monitoring tool for 6 months demonstrated lower usage rates (67 %) than those who also self-monitored and received feedback on progress (87 %).

4 Discussion

This study reviewed smartphone use in physical activity measurement and promotion research. Based on our data, physical activity studies that measured and aimed to influence physical activity using this technology were first published in 2007 [18, 21]. Increases in the rates of publication across our review period are also noticeable,

highlighting smartphone technology as an emerging and fast developing field of enquiry within physical activity research. This trend is likely to continue as smartphone technologies become more accessible (and acceptable) as a physical activity measurement and intervention tool.

The 26 studies identified covered a range of chronic diseases and non-clinical settings across the lifespan. Studies originated from a variety of highly ranked gross domestic product (GDP) countries [39], highlighting a need for research in lower- and middle-income nations, where mobile phone proliferation (which will include earlier- as well as later-generation smartphone technology) is highest [4]. A focus on lower socio-demographic groups in high-income countries, where low physical activity and health risks cluster [40], is also warranted, particularly given that these groups tend to use mobile phones the most [41]. Pratt et al. [42] support this position, and suggested that the greatest health potential of mobile phone technology rests with its capacity to reach populations with restricted access to interventions or healthcare information.

Physical activity data were monitored using external devices, native smartphone sensors, or a combination of both. Pedometers were the most commonly used external device, with step counts entered manually into the phone. Native mobile sensors improved activity recognition and real-time compliance measurement [43], although battery life may limit this approach over longer measurement periods [20]. We identified seven studies that used in-built mobile accelerometers [13, 15–17, 35, 36], and a variety of algorithms, to recognize physical activity (as well as transitions between sedentary and non-sedentary activities). These studies reported average-to-excellent levels of measurement accuracy, with the mobile phone placed mainly in the waist-to-hip area. Two of the most recent studies in this area reported that activities such as sitting, standing, walking, and jogging can be recognized with relatively high accuracy using an in-built tri-axial accelerometer, gyroscope [15, 16], and magnetic sensors [16]. However, measurement accuracy was mainly assessed with small samples completing a limited set of standardized activity trials. Future advances will see physical activity studies adopting statistical pattern recognition algorithms that use a combination of smartphone motion sensors [7], under free-living conditions with larger and more diverse samples.

Similar to a review on children and adolescents [10], and a meta-analysis of general mobile devices used for physical activity promotion [12], we found a lack of interventions based on behavioral change theories. In the present review, five smartphone intervention studies [19, 23, 25, 33, 37] evaluated physical activity effects—none of these studies connected in-built accelerometers and physical activity measurement to intervention processes, instead using pedometers and user-entered step counts as an

outcome measure. Further to this, measuring and influencing physical activity through a smartphone was related to weight reduction and improvements in other cardiovascular risk factors, as well as quality of life, although studies were few in number [27, 32, 33] and generally lacking a comparative or control group design. For physical activity specifically, step count changes were small (but positive and significant), and observed over short intervention and measurement periods, in small sample sizes. Evidence on intervention effectiveness is therefore limited, emerging, and in need of well designed studies that provide causal data on health risk and behavior change through in-built measurement sensors. Two recently published protocol papers provide encouraging indications that research is developing in this direction [44, 45]; both studies propose randomized controlled trial designs using in-built sensors and apps to measure and influence physical activity for chronic disease prevention and outpatient cardiac rehabilitation, respectively.

Participant perspectives and compliance were commonly assessed within intervention studies. Physical activity profiles, real-time feedback, social networking, expert consultation, and goal setting were identified as key features that facilitated physical activity engagement. Interestingly, a number of studies highlighted other features that limited engagement, such as disruptive prompts and auditory signals, text messaging, and competition-based strategies. Intervention compliance was higher when app rather than hard copy diaries were used, and even higher when objectively measured physical activity was connected to feedback and goal setting. Together, these findings highlight the importance of using smartphone features to promote engagement and compliance, a suggestion reinforced by Kirwan et al. [46], who advocate the need to pay special attention to app design, feedback, navigation, and terminology in order to maximize utility and ease of use.

In presenting our findings, we recognize a number of study strengths and limitations. This is the first study to comprehensively review data on smartphone technology and its use in physical activity measurement and promotion. We argue that these two processes are inextricably linked, and together provide new and exciting opportunities for real-time feedback and momentary (or point of decision) intervention strategies. The relatively small number of studies identified, which were characterized by poorer quality research designs, small sample sizes, and short study periods, was the main limitation of the present study.

5 Conclusions

The findings suggest that smartphone technology can accurately measure a range of behaviors. This, together

with the variety of novel and engaging intervention strategies used by smartphones, and user perceptions on their usefulness and viability, highlights the potential such technology has for physical activity promotion. We emphasize that the evidence base is emerging (if developing) and relatively limited. To better inform our understanding of effectiveness, and thereby strengthen translational efforts, well designed studies are needed that comprehensively assess physical activity measurement accuracy and long-term intervention effects. Importantly, researchers should undertake work with more diverse and appropriately powered samples and rigorous study designs.

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JBR, NDG, ST, APR, and RSC contributed to the design of the review protocol. JBR conducted the database search. Two reviewers independently performed the selection of articles (NDG and JBR) and examined the titles and abstracts of the identified references to exclude articles out of scope. Any disagreements on study inclusions were resolved through discussions with another reviewer (ST) and a consensus reached. JBR, NDG, and ST assessed the eligible papers, extracted the data, and discussed the findings. JBR drafted the paper and NDG, ST, APR, and RSC reviewed the manuscript and contributed to subsequent drafts. All authors read and approved the final review.

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