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Big data vs accurate data in health research: Large-scale physical activity monitoring, smartphones, wearable devices and risk of unconscious bias

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ABSTRACT

Fundamental to the advancement of scientific knowledge is unbiased, accurate and validated measurement techniques. Recent United Nations and landmark Nature publications highlight the global uptake of mobile technology and the staggering potential for big data to encourage people to be physically active and to influence health policy.

However, concerns exist about inconsistencies in smartphone health apps. Big data has many benefits, but noisy data may lead to wrong conclusions. In reaction to the increasing availability of low quality data; we call for a rigorous debate into the validity of substituting big data for accurate data in health research.

We evaluated the step counting accuracy of a smartphone app previously used by 717,527 people from 111 countries. Our new data (from 48 participants; aged 21–59 years; body mass index 17.7–33.5 kg/m^2) revealed significant (15–66%) undercounting by Apple phones. In contrast to the generally positive performances of wearable devices for stereotypical treadmill like walking, we observed extraordinarily large (0–200% of steps taken) error ranges for both Android and Apple phones.

Unconscious bias (developers' perceptions of usual behaviour) may be embedded into many unvalidated smartphone apps. Consumer-grade wearable devices appear unsuitable to detect steps in people with slow, short or non-stereotypical gait patterns. Specifically, there is a risk of systematically undercounting the steps by obese people, females or people from different ethnic groups resulting in biases when reporting associations between physical inactivity and obesity. More research is required to develop smartphone apps suitable for all people of the heterogeneous global population.

Introduction

Mobile technology has become ubiquitous. According to a 2010 United Nations report [1], in 2008, India had more mobile phones (545 million) than toilets (366 million people with access to improved sanitation). This illustrates widespread participation in the current mobile technology revolution. The technology enabling mobiles phones was developed in the 1940s but it was not until the 1990s that the brick-like phones were replaced by progressively thin and more fashionable models. Early health-related hypotheses for mobile technology included automatic call outs of emergency services for people experiencing cardiac arrest [2], revolutionizing care for people with cognitive impairments [3] and preventing dental caries [4]. In 2007, Apple unveiled the iPhone, which has helped popularise smartphones and led to the widespread use of third party apps.

Smartphone embedded sensors and the associated apps are becoming increasingly used in health research – making large-scale experiments feasible outside of the laboratory [5,6], In a 2017 *Nature* paper [7], daily steps were counted using a smartphone app [8] downloaded by 717,527 people from 111 countries across the globe. Obesity was also assessed using self-reported height and weight to calculate body mass index (BMI). The subsequent analysis of daily step counts showed that activity inequality (a measure describing how step counts are distributed within a country) was a good predictor of national obesity. Inactivity was shown to correlate with obesity and inactive females in Saudi Arabia were shown to be associated with the largest national activity inequality [7]. This landmark paper highlights the staggering potential for mobile technology and big data – to help curb the global pandemic of obesity, encourage people to be physically active and influence public health policy and urban planning [7].

However, the increasing use of smartphone embedded sensors and big data for large-scale experiments also draws attention to some fundamental questions [5,6,9]. To what extent should big data and remote self-reported health outcomes replace more accurate and validated clinical assessments for use in health research? Users have expressed concerns about privacy, the accuracy of smartphone apps and unvalidated apps providing inappropriate advice [6]. Big data has many benefits, but noisy big data can lead to wrong conclusions [10]. In the book, "Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy" [11], C. O'Neil discusses how the

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black box models often used to analyse big data can reinforce existing biases in society. When analysing large-scale physical activity data, we may therefore need to stay mindful of unconscious biases against larger people. Exercise has many health benefits and should be encouraged [12], but physical activity alone does not promote weight loss [13]. The causes of the current obesity pandemic are likely multidimensional and complex [13].

Hypothesis

We hypothesise unvalidated physical activity smartphone apps may substantially and systematically underestimate activity in vulnerable population sub-groups across the world. We contend it is time to better evaluate such apps and debate the consequences of substituting big data for accurate data in health research.

Evaluation of the hypothesis

Support for the hypothesis

Concerns exist about the accuracy of some smartphone apps and the technical limitations of different smartphones to provide continuous monitoring [5,6,9]. Several studies have evaluated the accuracy of consumer grade smartphone apps [14,15] and wearable devices [14–17] to measure physical activity during treadmill walking in controlled laboratory settings. Even for healthy young adults (mean age 32 years and BMI 22.6) large variations in both the validity and test-retest reliability of recorded step counts have been observed [14]. Errors are further compounded by slow (3.2 km/h) treadmill walking speeds [14]. Slower walking speeds (1.0–2.0 km/h) are particularly problematic for off-the-shelf devices that may miss 17–96% of steps [16]. The accuracy of these devices further deteriorates for non-stereotypical gait patterns. For people who have survived a stroke, Carroll et al. found that no steps were detected using pedometers at 6-minute walk test speeds slower than 1.8 km/h [17].

Most evaluations of wearable devices have been undertaken in a laboratory with participants walking on a treadmill, but laboratory-assessed and daily-life gaits are different [18] and may represent different domains of physical function [19]. Compared to laboratory gait, in the free-living context, people walk significantly slower and with more variability [18]. The step counting errors observed in laboratory settings [14–17] may further increase for remote-monitoring scenarios because in the real-world people walk with both slow and fast cadences (according to bimodal distributions) and complete far more short walks than long walks [20]. Across the global population (with its inherent variability) smartphone apps that have been designed for the average consumer are therefore unlikely to provide a valid and unbiased instrument for the scientific monitoring of physical activity [15].

Concerns also exist about the appropriateness of advice offered by unvalidated smartphone health apps [6]. Most validation studies of smartphone apps have used young healthy people, but health research often focuses on clinical cohorts. Transfer between these different cohorts is questionable. Previous research has established that training activity-recognition algorithms using data from young healthy people can result in smartphone apps that are unsuitable for older people [21]. Furthermore, the reported step counting errors from different wearable devices [14–17] appear to be dependent on the measured gait kinematics, parameters that depend on walking speed and age [14–17,22,23]. Importantly when comparing remotely assessed physical activity and health related outcomes across different countries, the measured gait kinematics may also depend on body mass index [23], gender [23,24], race [25] and preferred phone carrying positions [15,26]. This could, for example, lead to the systematic undercounting of walks by obese people, females, people from different ethnic or racial groups and people with different clothing or preferred phone positions.

Noisy big data can still lead to wrong conclusions [10]. It has been argued that the black box models often used to analyse big data (which includes proprietary step counting algorithms) risk reinforcing existing biases and increasing inequality [11]. Unconscious bias (the developer's perception of usual walking) programmed [11] into a smartphone app may favour steps taken during fast stereotypical (or treadmill like) walking. Reactivity (by participants to their recorded steps counts) may then further bias the internal validity of such activity data. Stereotypical walkers (for whom step counting apps are relatively accurate) may receive positive feedback about their activity levels, which could increase their intrinsic motivation [27] and lead to an increase in physical activity. Conversely, vulnerable people (for whom step counting apps may systematically undercount steps) may experience a decrease in intrinsic motivation [27]. This could lead to reduced physical activity and users abandoning the app [6].

Additional bias includes the sometimes inflated link between physical inactivity and obesity [13]. Exercise has been promoted as "the miracle cure" [12]. This may lead to beliefs about the "sin of physical inactivity" [28] and increase discrimination against larger people, who may be erroneously perceived as lazy. Extensive scientific evidence corroborates physical activity alone does not promote weight loss, "you can't outrun a bad diet" and "It is time to bust the myth of physical inactivity and obesity" [13].

Opposition to the hypothesis

Several studies have reported that both smartphones apps and wearable devices can accurately track steps taken on a treadmill [29,30]. It was concluded that such findings should reinforce trust in smartphones and underpin strategies to improve population health [29]. Sufficient accuracy has also been reported for people with Multiple Sclerosis; provided they walk fast enough and use a suitable device [30]. In a free-living context, a smart phone app has also been validated against a wearable activity monitor, but not validated against a gold standard (e.g. actual number of steps taken) [31].

Several studies have used wearable devices to remotely assess daily walking. Combined with cohort specific signal processing algorithms, wearable devices have been used to remotely detect steps and unstable movement patterns in high fall-risk older people [32–37], people with Parkinson's disease [37,38] and mild cognitive impairment [36]. New technology, machine learning algorithms, cloud computing and the use of crowd sourcing techniques may help overcome many remote monitoring performance limitations [5,9]. Together this suggests that accurate large-scale physical activity monitoring should be possible.

It is also well accepted that physical activity helps individuals to maintain a healthy weight [12,39]. Large-scale physical activity and obesity data recorded using a smartphone app [8] agree with previously reported relationships between age and gender as well as country-level variations in physical activity and obesity level [40–43]. Aggregated by country, a moderate LOESS (locally weighted smoothing) correlation ($r = 0.69$) was observed between the WHO obesity estimates (BMI ≥ 30) [43] and obesity based on smartphone recorded heights and weights [7,8] and a weak LOESS correlation ($r = 0.32$) between a World Health Organization (WHO) physical activity measure [42] and aggregated smartphone step counts [7,8].

Assessment of the smartphone app used for large-scale physical activity monitoring

With respect to large-scale physical activity monitoring, our review of the literature revealed no published validation for the smartphone app [8] used by 717,527 people from 111 countries [7]. Two studies were therefore undertaken in 2017 and 2018 to (i) evaluate the app's potential to accurately count steps and (ii) confirm our initial findings with respect to the app's step counting accuracy and reliability.

2017 Study: Sixteen university students with no known gait impairments (8 Apple users; 8 Android users; aged 21–27 years; height

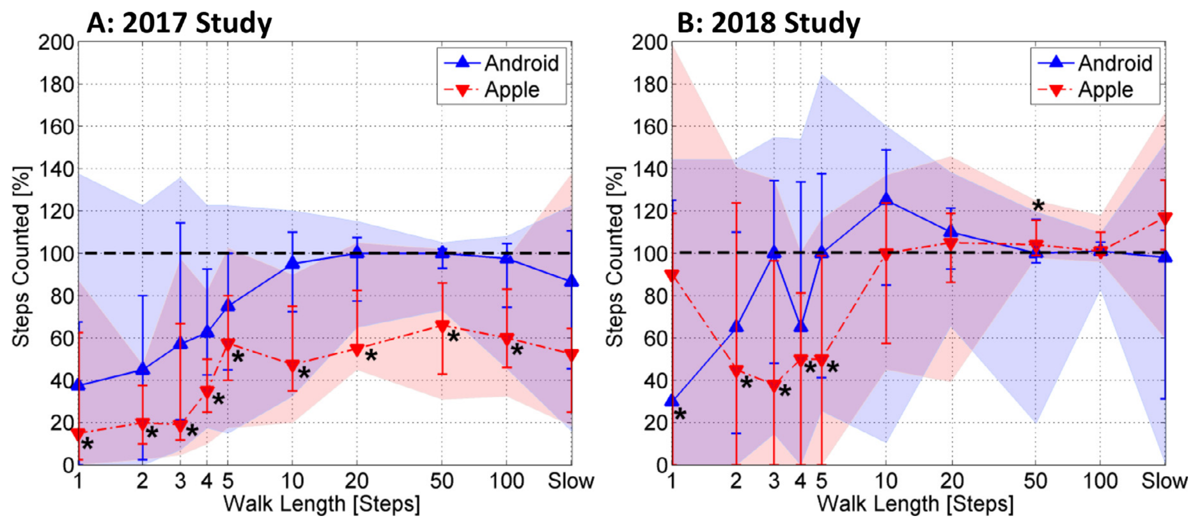

Fig. 1. Changing accuracy of different versions of the step counting app used for large-scale physical activity monitoring (8) under ideal conditions, medians (triangles), inter-quartile ranges (error bars) and 75% ranges (shaded regions) for Apple and Android phones were calculated. A: 2017 Study: For Apple, (*) indicates that the undercounting errors were significant for most walk lengths ($p \leq 0.05$). B: 2018 Study: For most conditions, the median percentage of steps counted increased relative to the 2017 study, although walks 2–5-steps in length were still undercounted by Apple phones.

154–192 cm; weight 44–90 Kg; body mass index 18.3–28.7 kg/m^2; 9 males and 7 females) agreed to participate and completed multiple walks of different lengths with their mobile phone fixed and upright against the sacrum between the posterior iliac spines. We considered that this location was ideal for recording the accelerations associated with both left and right steps while walking. At usual speed and over flat terrain each student completed: 20 by 1-step walks (1-step repeated 20 times with a 2-second rest between each walk); 10 by 2-step walks; 7 by 3-step walks; 5 by 4-step walks; 4 by 5-step walks; 2 by 10-step walks; a 20-step walk; a 50-step walk and a 100-step walk. Each student also completed a 100-step walk at a self-selected slow pace. Accuracy for each condition was calculated by dividing the number of steps recorded with the smartphone app [8] by the number of steps taken. The medians (triangles), interquartile ranges (25–75 percentiles, error bars) and 75% ranges (12.5–87.5 percentiles, shaded regions) were calculated [Fig. 1A]. The Wilcoxon signed rank test (an appropriate non-parametric statistic for non-normally distributed data and small samples) was used to determine if the recorded median percentages of step counts were different from 100% of the steps taken for each condition. Significance was set at $p \leq 0.05$ and annotated (*). Android phones included Samsung, OnePlus, Moto, Sony and Agora running Android 4.4 to 7.1 Apple phones included the iPhone 6s and SE running iOS 10.3 to 11.0.

2018 Study: An independent sample of 32 healthy participants with no known gait impairments were recruited. This sample comprised 19 Apple users; 13 Android users; mean age 21–59 years; height 155–191 cm; weight 50–102 kg; body mass index 17.7–33.5 kg/m^2; 11 males and 21 females. The study protocols and analyses for 2017 (described above) and 2018 were identical. Android phones in 2018 included Samsung, Sony, Oppo, Galaxy, Huawei, LG, Google and Agora running Android 4.4 to 8.1 Apple phones included iPhone SE, 6, 7 & 8 running iOS 10.3 to 11.4.

Results

In the 2017 study, the median accuracy across walks for Apple phones was 15–66% of steps counted [Fig. 1A]. Median accuracy for Android phones was 38–100% of steps counted. For Apple, (*) indicates that the undercounting errors were significant ($p \leq 0.05$). For Android, undercounting errors were not significant, even for the walks with fewer than 10-steps (large error ranges observed ensured sufficient overlap with 100%).

In the 2018 study, the median accuracy across walks for Apple phones was 38–105% of steps counted [Fig. 1B]. Median accuracy for Android phones was 30–125% of steps counted. Compared to the 2017 study, the median percentage of steps counted increased across most conditions. For Apple, (*) indicates significant ($p \leq 0.05$) undercounting errors (38–50%) for walks between 2-steps and 5-steps in length, and a significant over counting error (105%) for 50-step walks. For Android, (*) indicates 1-step walks were undercounted (30%).

In both studies, the error ranges for the percentage of steps counted increased for both slower and shorter walks. The large spread of performances (shaded regions) and increasingly inaccurate step counts for slow or short walks highlights that smartphone-recorded large-scale physical activity data may be low quality.

Discussion

Our findings agree with concerns about the technical limitations of different smartphones to provide accurate continuous monitoring and the inability of unvalidated health apps to provide appropriate advice [5,6,9]. Compared to the generally positive performances reported for laboratory-based treadmill walking [29,30] the extraordinarily large error ranges (shaded regions, Fig. 1A & B) imply that the measured gait kinematics (which depend on walking speed [15–17] phone position [15,26] gender [24] body mass index [23] age [22] and race [25]) may strongly influence the percentage of steps counted by consumer-grade smartphone apps. Furthermore, the differences in percentage of steps counted between the 2017 and 2018 studies suggests that phone updates and different app versions could also potentially change the outcomes of any smartphone-based assessments.

Laboratory-assessed and daily-life gaits are different [18]. The larger error ranges for slow or short walks observed in both studies are problematic because in daily-life people walk at slow and fast cadences (according to bimodal distributions) [20] and complete far more short walks than long walks [20]. With respect to large-scale physical activity monitoring, we need to be mindful that unconscious bias embedded [11] into black box smartphone apps may favour stereotypical (treadmill like) and faster walking. These issues present a risk of systematically undercounting steps for slower [14–17,30] and shorter walks; walks by larger people [23], females [24], people from different racial or ethnic groups [25], people with non-stereotypical gait [17,31] and different preferred phone positions [15,26].

For both Android and Apple, the larger error ranges observed in

2018 compared to 2017 (shaded regions, Fig. 1B versus A) may reflect increased diversity in the 2018 study population. Compared to the 2017 cohort (aged 21–27 years; body mass index of 18.3–28.7 kg/m^2) the 2018 cohort were aged 21–59 years and had a body mass index of 17.7–33.5 kg/m^2. Compared to the undercounting observed in 2017, a greater proportion of steps were counted in 2018, suggesting improved app accuracy for walks of at least 10-steps. However, the proportion of walks being over counted in 2018 may also have increased.

Limitations and future research recommendations

Limitations of our evaluation studies include the small sample sizes and the difficulty generalising results from cohorts of younger healthy participants from middle class backgrounds and predominately European ethnicity to people of all ages, ethnicity, body mass index, people with non-stereotypical gait patterns or who may use different preferred phone positions. With respect to large-scale physical activity monitoring, the large 75% error ranges observed under our relatively homogeneous testing conditions [shaded regions, 0–200% of steps, Fig. 1A & B] suggests greater inaccuracy would present in the more heterogeneous global population. Furthermore, the 75% error range used to assess the spread of errors is likely to be a conservative representation of the total error range, but the small sample sizes precluded the reliable calculation of a 95% error range. To definitively determine the extent that consumer-grade smartphone apps undercount non-stereotypical gait, walks by larger people, females, people from different ethnic groups, people with different preferred phone positions and different national dress, a much larger heterogeneous sample is required. Future research should focus on the development, training, testing and validation of more accurate algorithms for large-scale physical activity monitoring. This requires data from more people residing in different countries with a range of BMIs and should also include data from people with non-stereotypical gait patterns. Validation of step counting accuracy during the activities of daily living should be assessed against a gold standard at home and over multiple days.

Consequences of the hypothesis

Fundamental to the advancement of scientific knowledge is unbiased, accurate and validated measurement techniques. There is significant risk that unconscious bias (a developer's perception of usual behaviour) may be embedded [11] into many consumer-grade smartphone apps [7,8]. With respect to physical activity monitoring, this may favour fast stereotypical (treadmill like) walking. Outside of a laboratory; however, people walk with both slow and fast cadences, have more variable gait and complete far more short walks than long walks [18,20]. Consequently, across the global population (with its inherent heterogeneity) smartphone apps (if designed for the 'average' consumer) are unlikely to provide a valid or unbiased measurement instrument. Big data has many benefits. In a large data set white noise may cancel out and enable subtle trends to be observed, but low quality big data (particularly if it includes systematic measurement errors) may still lead to wrong conclusions [10]. We must stay mindful that the black box models sometimes used to analyse big data may reinforce society's existing biases [11]. This may include the sometimes inflated link between physical inactivity and obesity [13]. In reaction to the increasing availability of low quality unvalidated data; we call for a rigorous debate into the validity of substituting big data for accurate data in health research.

Author contributions

MB led the study, analysed the data and drafted the manuscript. MB, EP, AH, KL and ZC collected data. EP, AH, KL, ZC, SG and SL critiqued the manuscript. The authors declare no competing financial interests. The authors declare no competing financial interests.

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