# Validation of smartphone step count algorithm used in STARFISH smartphone application

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**Validation of smartphone step count algorithm used in STARFISH smartphone application**

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## Abstract

**BACKGROUND:** Smartphone sensors are underutilised in rehabilitation.

**OBJECTIVE:** To validate the step count algorithm used in the STARFISH smartphone application.

**METHODS:** 22 healthy adults (8 male, 14 female) walked on a treadmill for 5 minutes at 0.44, 0.67, 0.90 and 1.33 $m \cdot s^{-1}$. Each wore an activPAL™ and four Samsung Galaxy S3™ smartphones, with the STARFISH application running, in: 1) a belt carrycase, 2) a trouser or skirt pocket), 3a) a handbag on shoulder for females or 3b) shirt pocket for males and 4) an upper arm strap.

Step counts of the STARFISH application and the activPAL™ were compared at corresponding speeds and Bland-Altman statistics used to assess level of agreement (LOA).

**RESULTS:** The LOA between the STARFISH application and activPAL™ varied across the four speeds and positions, but improved as speed increased. The LOA ranged from 105–177% at 0.44 $m \cdot s^{-1}$; 50–98% at 0.67 $m \cdot s^{-1}$; 19–67% at 0.9 $m \cdot s^{-1}$ and 8–53% at 1.33 $m \cdot s^{-1}$. The best LOAs were at 1.33 $m \cdot s^{-1}$ in the shirt pocket (8%) and upper arm strap (12%) positions.

**CONCLUSIONS:** Step counts measured by the STARFISH smartphone application are valid in most body positions especially at walking speeds of 0.9 $m \cdot s^{-1}$ and above.



**Key Words**

Physical activity; step count; accelerometry; smartphone; walking

## 1. Introduction

Much of the world's population remains physically inactive [1] despite numerous physical activity guidelines aimed at promoting physical activity for healthy living [2, 3]. Innovation to increase physical activity is urgently needed and furthermore interventions to increase physical activity require accurate measurement tools.

An accelerometer is an inertial sensor designed to measure physical acceleration along a single axis. Modern Micro Electro Mechanical Sensor (MEMS) accelerometers are widely available in tri-axis packages that can be as small as a few square millimetres, allowing them to be attached to, or embedded within, a wide variety of objects including modern smartphones. Thus mobile phone applications (apps) can use the data from the embedded accelerometers as input for a range of algorithms capable of tracking and storing measurements of the intensity, frequency, pattern and duration of different types of activity [4]. Individuals may carry their phones in a variety of places on their person or in a bag. The algorithms have become more complex to take into account this variation of position, as device placement and hence orientation can affect accuracy [4]. The most common places where phones are worn, or carried, are in a trouser pocket, in a hand bag, in a strap on the upper arm, in a shirt pocket and in a case worn on the hip [5]. There have been calls to utilise the sensors in this ubiquitous technology to aid rehabilitation [6] in the same way tri-axial accelerometers have embraced [7].

STARFISH, a smartphone based application, was designed by our group, as a behavioural change intervention to encourage the user to become more physically active by increasing their daily step count [8]. In STARFISH, which uses the metaphor of a fish tank displayed as the wallpaper on the home and lock screens, groups of four people, receive real time feedback on their own physical activity and that of each member of the group. STARFISH is unique in that it does not require an external device like other apps, instead it uses the tri-axial accelerometer within the smartphone to record the user's step count and uploads the data to the STARFISH server. It is also unique as this data is then relayed to the other members of the group so they can see each other's progress in real time. STARFISH has been used in two pilot trials with older people [8] and stroke survivors [9] and is currently being used in a randomised control trial in stroke survivors.

At present, however, no validity data exist for the algorithm of this application. Therefore, the aim of this study was to evaluate the validity of the STARFISH app to measure steps taken by comparing it with the step count data from an activPAL™ device. The activPAL™ is valid in measuring step counts in both free living and laboratory conditions and is regarded as one of the gold standard devices in step count monitoring [10-12]. In addition, as device placement may affect the accuracy of the accelerometer within the phone, we sought to compare the validity of the step counts from the accelerometer whilst on different positions on the body.

## 2. Methods

A convenience sample of 22 healthy adults was recruited from friends and family of the research team; eight were male and 14 female, the mean age was 33.7 years (SD 7.1). After gaining written informed consent demographic information was obtained. An activPAL™ (PAL Technologies, Glasgow, Scotland) was then attached to the midline of the participant's anterior thigh using a PALstickie (double-sided hypoallergenic hydrogel adhesive pad) and the participant was asked to wear/carry four Samsung Galaxy S3™ mobile phones with the STARFISH application running in the following positions: 1) on the hip in a standard mobile phone carry case attached to a belt, 2) in a pocket (trousers or skirt), 3a) in a mid-sized handbag on their shoulder for females or 3b) in a shirt pocket for males and 4) attached to the upper arm using a strap.

Participants then walked on the treadmill at four different speeds for 5 minutes at each speed. Each participant walked at the following speeds in order from slowest to fastest: 0.44, 0.67, 0.90 and 1.33 $m \cdot s^{-1}$. These four speeds, range from slow to above average walking for those with long term neurological conditions [13-15]. Participants were informed every minute how much time was left and given a 30 second and 10 second warning before the end of each walking test. Participants were given a 2 minute rest between each speed, during which step count data from the STARFISH app was recorded. After the treadmill session the activPAL™ was removed and data downloaded using activPAL™ Process and Presentation version 7.2.32.

All treadmill sessions took place in the Human Performance Laboratory in the University of Glasgow. Ethical approval was given by the University of Glasgow's College of Medical, Veterinary & Life Sciences Ethics Committee.

## 2.1 Statistical analysis

Bland Altman statistics were used to describe the Level Of Agreement (LOA) between the activPAL™ step count and the step count of the STARFISH app with the smartphone in each position for each corresponding speed. These were the mean difference between the two measurements and the standard deviation (SD) of this difference and the upper and lower levels of agreement between the two measurements. LOA was expressed as a percentage of the mean activPAL™ step count for the corresponding speed. All statistical analysis was carried out using IBM SPSS Statistics version 22 and statistical significance was set at $p<0.05$.

## 3. Results

The smallest mean differences in step count between the STARFISH app and the activPAL™ were seen at higher walking speeds, especially 1.33 $m \cdot s^{-1}$. The LOA between the activPAL™ and the STARFISH app step counts also improved as speed increased.

The mean difference between the step count recorded by the activPAL™ and the STARFISH app was below 10% at all positions and speeds apart from in the trouser pocket at 0.67 and 0.9 $m \cdot s^{-1}$ and in the shirt pocket at 0.67 $m \cdot s^{-1}$ (Table 1).

All smartphone positions produced a LOA that was greater than 100% of the activPAL™ mean step count at 0.44 $m \cdot s^{-1}$. Compared to this lowest speed the LOA improved at all positions at 0.67 $m \cdot s^{-1}$ ranging from 50% when the smartphone was in the case on the upper arm to 98% in the case on the hip. The LOA continued to improve across all smartphone positions when the speed was 0.90 $m \cdot s^{-1}$. The LOA at this speed ranged from 19% when the smartphone was in both the hand bag and shirt pocket positions to 67% when the smartphone was in the trouser pocket. The best LOA for each smartphone position was seen at the highest speed of 1.33 $m \cdot s^{-1}$: 8% when the smartphone was in the shirt pocket, 12% in the case on the upper arm, 19% in the handbag, 23% in the case on the hip and 53% in the trouser pocket.

## 4. Discussion

The results show that the step count data derived from the accelerometer of the Samsung Galaxy S3™, when used by the STARFISH app had varying levels of agreement with the step count of the activPAL™ but generally improved with increasing walking speed. The mean difference between the two measurements was only over 10% when the smartphone was in the trouser pocket at 0.67 and 0.9 $m \cdot s^{-1}$ and in the shirt pocket at 0.67 $m \cdot s^{-1}$. The LOA between the activPAL™ and the STARFISH app step counts became stronger at higher walking speeds (0.9 $m \cdot s^{-1}$ and above) and was weakest at the lower speeds; being greater than 100% at 0.44 $m \cdot s^{-1}$ and ranging from 50-98% at 0.67 $m \cdot s^{-1}$. These slower two speeds tested (0.44 and 0.67$m \cdot s^{-1}$) are in the range of stroke survivors with limited community ambulation (0.4 – 0.8 $m \cdot s^{-1}$) [14]. However the faster walking speeds of 0.9 and 1.33 $m \cdot s^{-1}$ are comparable to the walking speed of those moderately impaired by Multiple Sclerosis (1.26$m \cdot s^{-1}$, SD 0.23) or Parkinson's (1.12 $m \cdot s^{-1}$, SD 0.20) [13, 15].

This study used methods similar to previous activity monitor validation studies with participants walking at speeds of 0.45, 0.67, 0.90 and 1.33$m \cdot s^{-1}$ [11, 16, 17]. The results of this study were similar to those validating other devices against accelerometers as agreement was stronger at speeds of 0.9 $m \cdot s^{-1}$ and above [16, 17].

Previously positions in which the phones were not 'attached' to the body were found to be less accurate in the measurement of physical activity [4] however more recent evidence suggests that carrying a phone in a handbag or pocket produces valid step count data [18]. Our results from the handbag position confirm this, even at the lower speeds. This is of relevance as a cross-sectional study found that in real living situations 60% of women carry their phone in their bag and 60% of men carry their phone in their pocket [5]. However, from our results, placement of the phone in the trouser pocket produced the largest mean difference and the largest LOA, especially at lower speeds which may be due to variances in trousers worn.

Consumer available physical activity monitors generally underestimate step counts [12] especially at lower speeds [19, 20] which is a phenomenon found in tri-axial accelerometers in general [21]. As smartphone step counting applications use the tri-axial accelerometer within the device the accuracy of these varies but becomes worse with slower speeds [22]. Our results were in line with this as the LOA became stronger with the slightly faster speeds. As this is a validation trial the results found will be used to increase the accuracy of the step count algorithm at slower speeds in the future.

Low-cost step counting apps such as these may in the future be used to deliver group interventions and increase physical activity in many population groups and also used as an adjunct to web and tele-rehabilitation by health professionals and exercise scientists. Furthermore this, or a similar app, may in the future, be used to collect more accurate epidemiological physical activity data on a large scale and replace flawed self-report measures that are heavily relied upon in reports such as the Scottish Health Survey in Scotland [23].

This study shows that the accelerometer data collected by the STARFISH app via the Samsung Galaxy S3™ accelerometer is valid in most body positions especially at walking speeds of 0.90 $m \cdot s^{-1}$ and above. More work is required to increase the validity of measuring physical activity at lower speeds.

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Table1. Mean step counts and Bland Altman statistics for STARFISH step counts at different smartphone positions.

| Speed ($ms^{-1}$) | | activPAL | Trouser pocket (n=22) | Case (on hip) (n=22) | Hand bag (n=14) | Shirt pocket (n=8) | Case (Upper arm) (n=22) |
|---|---|---|---|---|---|---|---|
| 0.44 | Step count (SD) | 335 (90) | 310 (170) | 306 (98) | 376 (122) | 356 (57) | 316 (133) |
| | Mean diff (SD) % | - | -7 (45) | -9 (34) | 10 (31) | 10 (27) | -6 (38) |
| | LLOA - ULOA (%) | - | -81, 96 | -58, 75 | -52, 71 | -63, 42 | -69, 80 |
| | LOA (%) | - | 177 | 133 | 123 | 105 | 149 |
| 0.67 | Step Count (SD) | 441 (43) | 377 (103) | 433 (118) | 527 (71) | 468 (52) | 444 (50) |
| | Mean diff (SD) % | - | -15 (22) | -4 (25) | 8 (15) | 19 (15) | 0 (13) |
| | LLOA, ULOA (%) | - | -29, 58 | -45, 53 | -21, 37 | -11, 48 | -26, 24 |
| | LOA (%) | - | 87 | 98 | 58 | 59 | 50 |
| 0.90 | Step Count (SD) | 527 (45) | 467 (97) | 521 (61) | 549 (48) | 513 (50) | 506 (47) |
| | Mean diff (SD) % | - | -11 (14) | -1 (5) | -3 (4) | 0 (4) | -4 (6) |
| | LLOA, ULOA (%) | - | -20, 47 | -10, 12 | -13, 6 | -9, 10 | -10, 20 |
| | LOA (%) | - | 67 | 22 | 19 | 19 | 30 |
| 1.33 | Step Count (SD) | 609 (45) | 576 (79) | 605 (57) | 633 (52) | 600 (47) | 607 (46) |
| | Mean diff (SD) % | - | -5 (10) | -1 (4) | 3 (4) | 0 (1) | 0 (2) |
| | LLOA, ULOA (%) | - | -19, 34 | -11, 12 | -5, 14 | -4, 4 | -6, 6 |
| | LOA (%) | - | 53 | 23 | 19 | 8 | 12 |

Bland Altman statistics: the mean difference between the STARFISH step count and the activPAL™ step count and the upper and lower LOA at each position and speed.

Abbreviations: SD: standard deviation; diff: difference; ULOA: upper level of agreement; LLOA: lower level of agreement; LOA: level of agreement.