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Identifying walking trips from GPS and accelerometer data in adolescent females

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Abstract

Background—Studies that have combined accelerometers and global positioning systems (GPS) to identify walking have done so in carefully controlled conditions. This study tested algorithms for identifying walking trips from accelerometer and GPS data in free-living conditions. The study also assessed the accuracy of the locations where walking occurred compared to what participants reported in a diary.

Methods—A convenience sample of high school females was recruited (N=42) in 2007. Participants wore a GPS unit and an accelerometer, and recorded their out-of-school travel for six days. Split-sample validation was used to examine agreement in the daily and total number of walking trips with Kappa statistics and count regression models, while agreement in locations visited by walking was examined with geographic information systems.

Results—Agreement varied based on the parameters of the algorithm, with algorithms exhibiting moderate to substantial agreement with self-reported daily (Kappa = 0.33–0.48) and weekly (Kappa = 0.41–0.64) walking trips. Comparison of reported locations reached by walking and GPS data suggest that reported locations are accurate.

Conclusions—The use of GPS and accelerometers is promising for assessing the number of walking trips and the walking locations of adolescent females.

Keywords

walking behavior; physical activity measurement; self-reports; youth

Introduction

Our understanding of the importance of walking for physical activity and health has increased over the last two decades[1, 2]. Predominant tools for collecting walking data include direct observation, self-reports, and use of pedometers. Recently, researchers have explored the use of accelerometer data to identify walking activity with moderate success[3–5]. Furthermore, reliance on accelerometers or pedometers alone does not allow identification of individuals' location when walking. Understanding the context in which walking occurs is important because interpersonal, organizational, community, and environmental factors are expected to influence both physical activity and obesity[6].

The advent of global positioning systems (GPS), which record locational information over time, has stimulated research on walking and where it occurs [7, 8]. Combined with diaries, GPS data have been used to examine agreement of duration of visits at various locations [9], identify routes taken [10, 11], assess the accuracy of travel diaries [10], and quantify the underreporting of motorized travel [10]. Recent studies have used GPS to measure walking behaviors [12, 13] and to document where they occur [9, 14].

Combining accelerometer data with GPS data has been shown to be useful in quantifying walking activity[15, 16] beyond what GPS [13] or accelerometers [5, 17] can reveal independently. However, studies that have combined accelerometers and GPS to identify walking have done so in carefully controlled conditions. No research has examined the combination in free-living conditions.

The principal aim of this study was to develop and test algorithms to identify walking trips from accelerometers and GPS. We compared the walking trips extracted from the accelerometer/GPS combination with data self-reported in a diary. A secondary aim of the study was to compare the locations of walking trips indicated by the GPS/accelerometer data and reported in the diary. We hypothesized that the algorithms would have moderate agreement with the walking trips and their locations reported in the diary. We also hypothesized moderate to high agreement between the locations visited by walking that was self-reported in the diary compared to walking recorded on the accelerometer.

Methods

Study sample

The Trial of Activity for Adolescent Girls-2 (TAAG2) is a study of physical activity and nutrition behaviors of adolescent females in San Diego, CA and suburban Minneapolis/St. Paul, MN. Participants were part of the control condition of the original TAAG Study[18, 19]. For this study, a convenience sample (N=51) was recruited in 2007. In California, 26 females who attended one area high school and who were participants in the intervention condition of the TAAG Study were recruited[18]. In Minnesota, 25 students of two area high schools, who were not in the TAAG Study, were recruited. The Minnesota schools were similar in socio-demographic characteristics and location (roughly suburban) to high schools in which TAAG2 participants matriculated. Approximately half of the participants were in the 10th grade and half in the 11th grade. The study was approved by Institutional Review Boards at each site. All participants gave written assent and their parents provided written informed consent.

GPS and accelerometer measurement

Participants were given off-the-shelf Foretrex 201 portable (83.8 × 43.2 × 15.2 mm) GPS units (Garmin Ltd., Olathe, KS). These units have been shown to have adequate accuracy and reliability in free-living conditions [7]. An internal non-volatile memory card provides the unit with the capacity to store 10,000 points before the data require downloading. The units were set to record the positional coordinates of their location at 60-second intervals with the Wide Area Augmentation System (WAAS) disabled. The map datum used was World

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Geodetic Survey 1984 and the position format was latitude and longitude in degrees and minutes (HD° MM′).

Concurrently with the GPS unit, participants wore an accelerometer: the dual-mode ActiGraph model 7164, formerly known as the Computer Science and Applications (CSA) and Manufacturing Technology Inc. (MTI) (Pensacola, FL). Previous studies have demonstrated the ActiGraph to be a technically reliable instrument, able to detect differing levels of intensity[20, 21]. Accelerometers were set to record activity in 30-second epochs to maintain consistency with the methods used in the TAAG Study. We attempted to have the GPS record data at 30-second intervals but this compromised battery life, and so the GPS recorded at 60-second intervals.

Participants were asked to wear the GPS unit and accelerometer during all waking hours for six consecutive days, except when showering, bathing, swimming, or engaging in other activities that would result in submerging the units in water. They were instructed to wear the Actigraph unit on the right hip [22, 23]. They were instructed to carry the GPS units on either their wrists or on a belt around their waists, and to charge the GPS unit overnight every night. Study staff retrieved the devices, downloaded the data, and collected participant information on their experiences with carrying the devices.

Diary measurement

The Neighborhood Places Log (NPL) is a travel diary in which participants recorded information about travel outside of home or school. In the development of the diary, a pre-pilot with a convenience sample (six participants in California and seven participants in Minnesota) unrelated to the pilot sample was conducted to test the instrument. Pre-pilot participants were asked to fill out the diary and wear the GPS and accelerometer. The participants provided feedback to identify needed improvements to the diary.

In its final version, the diary included every place participants traveled to daily, their travel mode (e.g., walk/run, city bus, school bus, driven by someone else), times of arrival to and departure from a destination, the name of the destination, its address, and related information. Participants had the option to record the diary data on a PDA device or by hand on a paper version (Figure 1) for the same six days they wore the GPS and accelerometer.

Data processing and algorithm

The GPS-recorded data, including latitude, longitude, date, and time of day, were downloaded using an interface unit to a personal computer using MapSource Trip & Waypoint Manager (Garmin Ltd., Olathe, KS). Each GPS data file was cleaned with a Java program developed for this study. This procedure removed data headers, removed the first row of data (which includes considerable measurement error), converted coordinate information into decimal degrees, and transformed the data into wide-character ASCII format to enable further processing with geographic information system (GIS) software.

Accelerometer data were downloaded using a reader interface unit and the Computer Science and Applications Inc. RIU64k. exe Software Version 2.15c (Pensacola, FL). A computer program was used to identify and summarize valid data and walking episodes by participant. After receiving the accelerometer, a participant was presumed to be wearing the accelerometer from the time when the first non-zero value was recorded and was followed by one or more non-zero values being recorded. A participant was considered not to be wearing the accelerometer if 20 or more consecutive minutes had zero counts [24]. We considered counts exceeding 15,000 for 5 minutes or more as outliers, but none were identified. The program also merged each participant's accelerometer data with the corresponding GPS data according to the date and time information in each unit. Diary data entered into the PDAs were downloaded using Pendragon Forms 5.1. Hand-recorded diary data were manually entered into a database for two participants.

To identify walking trips, we used count and bout length information from the accelerometers. Counts register activity intensity over a period of time called an epoch, with higher counts corresponding to higher average activity over the epoch. Bouts are consecutive minutes of activity exceeding a given count. We defined a walking bout as consecutive minutes of activity at or exceeding 631 or 899 counts per 30 seconds. These thresholds corresponded to 97.5% and 84% of all slow walking activity among adolescent females, respectively[25]. We also considered bouts of at least 3, 5 and 10 minutes to define a walking episode. Each walking episode had a 30% tolerance for counts not meeting the threshold values. For example, in a 15-minute episode, 5 minutes could be under the threshold level and still count as a walking bout.

We also used speed and dwell time information from GPS data to identify walking trips. Consistent with prior research[10, 26], for the GPS data we used the amount of time between sets of consecutive GPS points (which we call dwell time) to separate walking trips from non-walking trips. We examined dwell times of at least 0, 3, 5, and 10 minutes. The GPS data contain speed estimates from one point to the next, so we used the range of speeds over an entire trip, with higher speed ranges suggesting a lower likelihood of walking activity. We tested criteria that all points should be within 1.6 km/h and 6.4 km/h (1 and 4 mph), and between 1.6 km/h and 9.6 km/h (1 and 6 mph). Altogether, we tested 48 ($2 \times 3 \times 4 \times 2$) different combinations of the accelerometer and GPS parameters. Both the GPS and the accelerometer criteria were to be met for a walking trip to be identified. Table 1 summarizes seven alternatives that capture variations among parameters used to detect walking trips.

Statistical analysis

A day was considered valid if the accelerometer was worn for more than 8.3 hours on a weekend day, 10.6 hours on a week day, consistent with the TAAG Study [27] and that day contained at least one GPS data point. Each day of data was evaluated for wearing time below the minimum wearing time threshold and if positive, it was excluded from analysis. Similarly, all activities occurring during school hours were excluded from the above analyses.

To develop and test algorithms to identify walking trips from accelerometers and GPS, the general analytical approach was to use a split-sample validation. Accordingly, we randomly divided the sample of participants into ‘calibration’ group and ‘validation’ groups.

To compare walking trips reported in the diary with those derived from the GPS and accelerometers combination, we summarized the data in two ways: the daily count of walking trips and the total count of walking trips reported by each participant during their valid days. Both variables are integer-valued counts, with theoretical minimum of 0 and an infinite maximum. The unit of analysis in the first is the person-day. When the data are aggregated across days, the unit of analysis is the person.

In the calibration sample, weighted Kappa statistics and count regression models (Poisson or negative binomial) were used to select the preferred combination of parameters to identify walking trips. The number of trips (daily or total) reported in the diary and the GPS/accelerometer are the dependent variable and independent variables, respectively, in the regression model. For each combination of GPS/accelerometer parameters, we estimated both a Kappa statistic and a regression model. The potentially large number of zeroes justifies the choice of these methods over other options such as concordance statistic or a Pearson correlation coefficient. To interpret Kappa statistics we followed the ratings suggested by Landis and Koch [28]: 0–0.2 poor, 0.2–0.4 fair, 0.4–0.6 moderate, 0.6–0.8 substantial, and 0.8–1.0 almost perfect. To interpret the results from regression, we used the Bayesian Information Criterion (BIC), a measure of model fit. Lower (or more negative) values indicate better fit. Raftery[29] suggests that the evidence favoring one regression model over another is weak, positive, strong, or very strong if the absolute difference in the BIC for two models is 0–2, 2–6, 6–10, or >10, respectively.

It is possible that agreement for individual trips may be low even though daily or total aggregates suggest high agreement. Therefore, we also assessed agreement of individual trips by reporting the number of matched and non-matched trips. A matched trip is defined as being identified through both methods and having agreement in both day and time-of-day (AM, PM). Non-matched trips were either not detected by the GPS/accelerometer while reported in the diary, or detected by the GPS/accelerometer but not reported in the diary.

The best-fitting algorithm to detect walking trips from the GPS/accelerometer combination is one with the highest Kappa statistic, the lowest BIC, the highest match rate, and the lowest non-match rate. All algorithms were re-estimated with the validation sample, and Kappa statistics, the BIC, and the rate of matched and unmatched trips were compared among different algorithms. All calculations were performed in Stata SE 9.2 (College Station, TX).

To achieve our secondary aim of examining agreement regarding the locations visited by walking trips, conditional on having been matched by the methods, we imported the GPS data of all walking trips to ArcMap 9.2 (ESRI, Redlands, CA). For each walking trip we drew a 0.4 km circle around the last GPS data point. All street names fully or partially contained in the circle were identified using ESRI Streetmap in ArcCatalog (ESRI, Redlands, CA). The street address associated with each destination in the diary was compared to the list of streets gathered from the GPS. A successful match occurred when the same street was found in the circle and the diary. When no street name was given in the diary, the name of the destination was hand-coded and identified on the map using additional diary information such as the trip length. Only one trip lacked street or destination names in the diary.

Results

Participants in the Twin Cities were all white, while 88% of San Diego participants were Hispanic (various races). Of the 51 participants, five were excluded because they lacked GPS data (two failures, one corrupted file, two not worn), three because they did not complete the diary, and one because her accelerometer data were recorded for less than what was required for every day. This reduced the sample to 42 participants, yielding a cumulative total of 252 days (42 × 6). Of these, 58 days were not considered valid because participants wore the accelerometer less than the threshold for a valid day, and 19 days had no GPS data records. The final sample contained 181 days for 42 participants. Participants assigned to the ‘calibration’ group had 92 participant-days of data, while those in the ‘validation’ group had 89. Participants reported an average of 0.54 walking trips per day. At the extremes, no walking trips were reported for 122 person-days (67.4%) and four walking trips were reported for two person-days (1.1%).

Results of a sample of parameters tested to identify walking trips in the calibration sample are shown in Table 2. For daily trips, Kappa statistics ranged from 0.40 to 0.48, suggesting moderate agreement. Alternatives 5 through 7 appeared to have the highest agreement, although they are statistically indistinguishable from each other. The BIC fit statistics for the count regression models ranged from −18.58 to −36.57. Pseudo-R^2 statistics were between

0.12 and 0.21 (not shown). Comparisons of the BICs across the regression models suggest positive, strong, and very strong evidence that alternative 4 is the algorithm that produces the best fit with the self-reported diary data.

When the trips are aggregated to the person level, Kappa statistics increase and lie between 0.41 and 0.64, suggesting moderate to substantial agreement. BIC statistics ranged from −2.69 to −12.98 and pseudo R^2 statistics ranged from 0.06 to 0.18. With these results, alternative 4 continued to exhibit the best fit of the seven algorithms shown.

Agreement statistics for the validation sample (Table 3) are slightly lower than for the calibration sample. At the person-day level, Kappa statistics ranged from 0.33 to 0.48, indicating fair to moderate agreement depending on the algorithm. The BICs from the count regression models ranged between −11.57 and −15.51, which does not provide strong evidence that a single algorithm is substantially better than the others. At the person level, Kappa statistics ranged between 0.47 and 0.59, suggesting moderate agreement. Figure 2 displays predicted and observed counts for alternative 4 with the calibration and validation data and the daily and total trip outcomes. BICs ranged between −7.22 and −8.87, also providing strong evidence that no single algorithm is superior. Together the results of the best-fitting algorithms to identify walking trips from the GPS/accelerometer combination suggest moderate agreement with self-reported walking trips.

The number of individual trips in the calibration sample that were successfully matched ranged between 18 and 29. This translates into a match level ranging between 37% and 59% of all the diary-reported trips, and between 49% and 78% of the GPS/accelerometer identified trips. In the validation sample, between 16 and 25 trips were matched, or between 33% and 51% of all diary trips and between 42% and 67% of all GPS/accelerometer trips were matched.

The results for our secondary aim to examine agreement among the locations visited by walking trips, conditional on being matched by the GPS/accelerometer combination and the diary, indicated substantial agreement (Table 4). In the calibration sample, depending on the parameters used to identify walking trips, between 91% and 100% of all matched trips agreed on location. In the validation sample between 86% and 88% of all matched trips agreed on location.

Discussion

This study developed methods to identify walking trips from a combination of GPS and accelerometers and subsequently examined agreement between the location of walking trips identified with these methods compared to self-reports in a diary among adolescent females under free-living conditions. Overall, we found agreement between the algorithms and diary self-reports to be largely a function of the parameters selected in the algorithm, ranging between moderate and substantial agreement. For walking trips that were matched, we found high agreement between the destination location reported on the diary and recorded on the GPS. This implies that locations and establishment names reported in the travel diary are accurate.

The main contribution of this study was the use of the combination of GPS and accelerometers to identify walking trips in free-living conditions. One previous study with GPS data found that 86% of trips identified from the GPS data were found in the diary and 77% of trips reported in the diary were identified in the GPS data [30]. However, that study focused exclusively on time periods that had GPS data available. Using similar methods and a different diary, but focusing on the entire day regardless of whether there was GPS data and adding the accelerometer, this study identified more unreported walking trips, thereby decreasing the overall match rate.

The methodology developed is simple and easy to implement. However, there is a growing list of data mining tools that could be applied to this type of classification problem and that may improve the ability to detect walking trips. Other accelerometer-only studies have used artificial neural networks [3, 31, 32], classification trees [4], various types of discriminant analysis[5], and Bayesian classification approaches[4, 5] to classify the activity type. They generally have been able to classify between 77 and 88% of all activities examined. Comparison of these methodologies to the algorithm described provide avenues for future research.

Among the parameters tested (Table 1), alternatives that included dwell time > 0 and wider speed and accelerometer count ranges seemed to perform better in terms of the agreement measures examined in this group of high-school age females. Specifically, alternatives 4, 5 and 6 were consistently superior to other alternatives. Consistent with the agreement statistics, Figure 2 visually displays how model fit is best with the calibration data and with the number of walking trips per day per person outcome.

The three best-fitting alternatives also embody different analytical tradeoffs. Alternatives 5 and 6 were more stringent in the parameters and therefore identified fewer trips than alternative 4. When a trip was identified with alternatives 5 and 6, that trip was more likely to be reported in the diary than when a trip was identified with alternative 4. The tradeoff is that there were many diary-reported trips that alternatives 5 and 6 missed. Thus, as the number of trips identified with the GPS/accelerometer combination increases, the number of these trips not reported in the diary also increases. Conversely, as the number of trips identified with GPS/accelerometer decreases, the number of unreported trips in the diary decreases. This pattern held in both the calibration and validation samples.

The pattern of agreement identified here mimics similar patterns of previous studies for travel diaries and vehicle-based GPS. In those studies, however, agreement was higher partly because the on-vehicle GPS units served mostly as a gold-standard (except for urban canyons and tunnels), since they operate only when the vehicle is running. Other researchers[10] found that 7% of GPS trips were not matched to a diary, and that of 40 vehicular trips reported in the diary, 8.6% could not be matched to GPS. A different study also using GPS in vehicles found that 9% of trips were not in the diary and 6% of diary trips were not matched to GPS[26]. In addition to blocked views from the sky, a special challenge in our case that may lead to not detecting trips, even when they are reported in the diary, is being able to distinguish walking trips from any movement detected by the GPS unit. For example, a walking bout may be confused with bicycling at low speeds or standing on a bus moving slowly through traffic.

Several other factors contributed to limitations in the matching rates. First, self-reported data from travel surveys tend to underestimate the number of trips and distance traveled [33–35], with face-to-face follow-up methods producing the fewest underreports [10]. Short trips tend to be underreported; frequent travelers, those under the age of 25, and those who are students or employed part-time tend to underreport the most [10]. Thus, walking trips, which tend to be short and less memorable than auto trips, are underreported in diaries. Second, walking trips as defined in the diary and identified by the GPS/accelerometer algorithms tend to be fairly rare or at least underreported events. For example, no such trips were reported on 67.4% of the days. These two factors may explain the seemingly low average number of reported trips per day (0.54), which is consistent with national figures on walking trips per day for this age group[36].

A third reason that may limit the number of matches is that walking appears to be inherently difficult to classify based on GPS and accelerometer data. One study found that almost three-quarters of activities such as lying down, sitting and standing, walking, running, cycling with an exercise bike, rowing with a rowing machine, playing football, Nordic walking, and cycling were correctly classified with GPS/accelerometer data, but among those, walking was the hardest to classify, with a 30% accuracy [15]. To complicate matters further, many walking episodes, such as from an automobile parking space to a building, may appear as walking trips in the GPS/accelerometer data based on the parameters defined, but they usually do not register as a walking trip when self-reported.

Another distinctive feature relative to prior research is that this study collected data over a six-day period. Du and Aultman-Hall (2007) showed important differences between 1-day and multi-day diaries. The emphasis on multiple days of monitoring is important to overcome data loss associated with GPS signal dropout and non-compliance with the accelerometer protocol [11]. Similarly, the accuracy of self-reported walking activity is questionable, as respondents have a tendency to not report certain types of trips, like routine walking trips, in multi-day travel diaries[37].

The current study has important limitations. First, it is unknown whether the algorithms and behaviors of the study sample of adolescent females can be generalized to the population or other subgroups. Furthermore, the relatively small sample size in this pilot study makes it difficult to conduct subgroup analyses. Second, different ranges for parameters outside of those used here may yield better-fitting algorithms. We limited our speed and accelerometer count ranges and the dwell times to parameters derived from previous studies. It is possible that different ranges and times may result in algorithms that are more sensitive and specific relative to self-reported information. This may be especially true for studies that include participants in different age ranges, and include male as well as female participants. Third, it is possible that the order in which the parameters in each algorithm are applied may influence the number of trips identified from the data. Fourth, we did not explore the instances in which there was not a match between the GPS/accelerometer and self-reports, which could derive from unreported shorter trips, or because they tended to have speeds that were beyond the ranges in the algorithms' parameters. Fifth, it is possible that the diary and the GPS/accelerometer underestimate total walking. There may be walking trips, such as walking in a mall, which may be missed with both data sources.

Conclusions

The use of GPS and accelerometers in combination is promising for assessing the number of walking trips and the walking locations of adolescent females. Although the agreement varied based on the input parameters of the algorithm, we found moderate to substantial agreement between the number of walking trips concurrently self-reported in a travel diary and identified through passive, portable GPS/accelerometer units. For trips jointly self-reported and identified with the GPS/accelerometer combination, there was substantial agreement between the diary location of the destination of each walking trip and what the GPS recorded.

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Day	Time Arrived (Include am/pm)	Time Left (Include am/pm)	Place	How did you get there (enter code)	Address or Intersection

Who was with you? (enter code)	Activity (enter code)	Everything you ate or drank at or from this place. If you didn't eat or drink, write "no".	$ you spent on food or drink	How you paid (enter M or C)

Figure 1.
Sample travel diary

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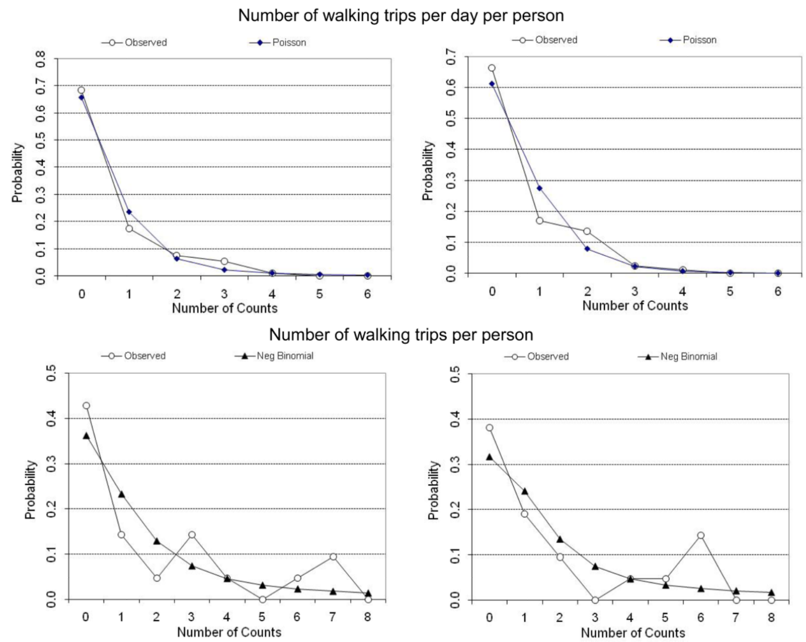

Figure 2.
Fit between observed and predicted counts for calibration (left) and validation (right) samples, alternative 4.

Table 1

Sample of parameters used to identify walking trips from GPS/Accelerometer combination

Alternative	GPS/Accelerometer parameters			
	Count p. 30 s^{-1}	Min bout (minutes)	Min dwell time (minutes)	Speed range (kph)
1	899	10	5	<6.4 & >1.6
2	899	5	0	<6.4 & >1.6
3	899	5	5	<6.4 & >1.6
4	899	5	5	<9.6 & >1.6
5	631	10	3	<9.6 & >1.6
6	631	10	5	<9.6 & >1.6
7	899	5	10	<6.4 & >1.6

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Table 2

Walking trip agreement between the travel diary and the GPS/Accelerometer combination, calibration sample (n=21 participants; 92 participant-days)

		BIC from count regression model		Kappa statistic		Matched trips	Unmatched trips	
Alternative	Trips (#)	Trips p. day p. person	Trips p. person	Trips p. day p. person (95% CI)	Trips p. person (95% CI)	(#)	GPS/accel Y Diary N(#)	GPS/accel N Diary Y(#)
1	23	−18.58	−2.69	0.40 (0.34,0.52)	0.41 (0.29,0.58)	18	5	31
2	59	−30.83	−9.82	0.41 (0.31,0.46)	0.59 (0.45,0.62)	29	30	20
3	54	−33.67	−12.94	0.42 (0.32,0.44)	0.63 (0.45,0.71)	28	26	21
4	55	−36.57	−12.98	0.43 (0.40,0.52)	0.64 (0.30,0.73)	28	27	21
5	33	−23.22	−5.11	0.48 (0.34,0.58)	0.57 (0.31,0.69)	21	12	28
6	34	−24.50	−5.83	0.48 (0.27,0.54)	0.57 (0.51,0.68)	21	13	28
7	51	−29.02	−11.34	0.47 (0.32,0.63)	0.62 (0.31,0.68)	28	23	21

Asymptotic 95%confidence intervals shown

49 walking trips in the calibration sample were recorded in the NPL diary.

Count regression model is a Poisson regression for trips per person per day and a negative binomial regression for trips per person.

Table 3

Walking trip agreement between the travel diary and the GPS/Accelerometer combination, validation sample (n=21 participants; 89 participant-days)

		BIC from count regression model		Kappa statistic		Matched trips	Unmatched trips	
Alternative	Trips (#)	Trips p. day p. person	Trips p. person	Trips p. day p. person (95% CI)	Trips p. person (95% CI)	(#)	GPS/accel Y Diary N(#)	GPS/accel N Diary Y(#)
1	25	−11.57	−7.28	0.33(0.30,0.41)	0.49 (0.10,0.62)	16	9	33
2	57	−15.51	−7.66	0.46(0.42,0.55)	0.47 (0.42,0.66)	24	33	25
3	54	−14.83	−7.56	0.48 (0.32,0.58)	0.53 (0.44,0.55)	25	29	24
4	55	−14.40	−7.29	0.47 (0.35,0.70)	0.51 (0.39,0.59)	25	30	24
5	35	−14.87	−8.87	0.45 (0.33,0.48)	0.59 (0.37,0.69)	22	13	27
6	33	−13.05	−8.37	0.43 (0.35,0.60)	0.57 (0.38,0.59)	22	11	27
7	51	−13.80	−7.22	0.41 (0.27,0.51)	0.58 (0.47,0.65)	23	28	26

Asymptotic 95%confidence intervals shown

Count regression model is a Poisson regression for trips per person per day and a negative binomial regression for trips per person.

49 walking trips in the validation sample were recorded in the NPL diary.

Table 4

Location agreement conditional on matching a trip with GPS/accelerometer and self-reports

	Calibration			Validation		
Alternative	**Matched trips (#)**	**Location agreed (#)**	**Location agreement rate (%)**	**Matched trips (#)**	**Location agreed (#)**	**Location agreement rate (%)**
1	18	18	100.0	16	14	87.5
2	29	27	93.1	24	21	87.5
3	28	26	92.9	25	22	88.0
4	28	26	92.9	25	22	88.0
5	21	19	90.5	22	19	86.4
6	21	19	90.5	22	19	86.4
7	28	26	92.9	23	20	87.0

Matched trips refer to the trips matched between the GPS/accelerometer combination and the self-reported trips.