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Validity of PALMS GPS Scoring of Active and Passive Travel Compared to SenseCam

Jordan A. Carlson, **Marta M. Jankowska**, **Kristin Meseck**, **Suneeta Godbole**, **Loki Natarajan**, **Fredric Raab**, **Barry Demchak**, **Kevin Patrick**, and **Jacqueline Kerr**
University of California, San Diego, San Diego, CA

Abstract

Purpose—To assess validity of the Personal Activity Location Measurement System (PALMS) for deriving time spent walking/running, bicycling, and in vehicle, using SenseCam as the comparison.

Methods—40 adult cyclists wore a Qstarz BT-Q1000XT GPS data logger and SenseCam (camera worn around neck capturing multiple images every minute) for a mean of 4 days. PALMS used distance and speed between GPS points to classify whether each minute was part of a trip (yes/no), and if so, the trip mode (walking/running, bicycling, in vehicle). SenseCam images were annotated to create the same classifications (i.e., trip yes/no and mode). 2×2 contingency tables and confusion matrices were calculated at the minute-level for PALMS vs. SenseCam classifications. Mixed-effects linear regression models estimated agreement (mean differences and intraclass correlations [ICCs]) between PALMS and SenseCam with regards to minutes/day in each mode.

Results—Minute-level sensitivity, specificity, and negative predictive value were ≥88%, and positive predictive value was ≥75% for non mode-specific trip detection. 72–80% of outdoor walking/running minutes, 73% of bicycling minutes, and 74–76% of in-vehicle minutes were correctly classified by PALMS. For minutes/day, PALMS had a mean bias (i.e., amount of over or under estimation) of 2.4–3.1 minutes (11–15%) for walking/running, 2.3–2.9 minutes (7–9%) for bicycling, and 4.3–5 minutes (15–17%) for vehicle time. ICCs were ≥.80 for all modes.

Conclusions—PALMS has validity for processing GPS data to objectively measure time walking/running, bicycling, and in vehicle in population studies. Assessing travel patterns is one of many valuable applications of GPS in physical activity research that can improve our understanding of the determinants and health outcomes of active transportation as well as its impact on physical activity.

Keywords

bicycling; geography; physical activity; transportation; vehicle; walking

Corresponding author: Jordan A. Carlson, Family and Preventive Medicine, University of California, San Diego, 3900 5th Ave. Suite 310, San Diego, CA 92103 USA, jacarlson@ucsd.edu, phone: 619-260-5542, fax: 619-260-1510.

Conflicts of Interest
The authors have no conflicts of interest. The results of the present study do not constitute endorsement by ACSM.

INTRODUCTION

Objective measurement of physical activity with accelerometers has become the preferred method of physical activity assessment in current research and is being used in large population studies such as the U.S.'s National Health and Nutrition Examination Study (22). A limitation of accelerometry is that types and domains of physical activity cannot be identified, including walking and active transportation. Researchers often use self-report questionnaires to assess active transportation and walking (e.g., IPAQ)(3). These tools provide a more specific and relatable outcome than total physical activity when investigating associations between built environments and physical activity because built environments are typically more strongly associated with active transportation than total physical activity (19). However, recent advances in Global Positioning Systems (GPS) technology allow researchers to use GPS devices to objectively assess walking, bicycling and vehicle trips, and systems such as the Personal Activity Location Measurement System (PALMS) improve feasibility of using GPS by reducing and simplifying data processing (18).

PALMS is a web-based software used by researchers across the world for processing GPS data and identifying trips and trip mode (i.e., walking/running, bicycling, driving) (11, 20). GPS data are uploaded directly into the PALMS system, which incorporates a user-friendly design with drop-down menus that allow users control over parameter settings that determine thresholds for the algorithms. The PALMS trip detection and classification algorithms incorporate GPS variables such as speed and distance between GPS points. The algorithms were developed using empirical testing and aspects of existing algorithms from health research (2, 10, 23, 26) as well as those from engineering, geography and transportation (6, 7, 16, 21).

The present study aimed to test criterion validity of the PALMS trip detection and mode classification algorithms for processing GPS data. While there currently is no gold standard criterion measure for trip detection, other existing GPS algorithms were validated using self-report as the comparison measure (2, 6, 7, 8, 16, 21, 23, 25, 27). We took the novel approach of using annotated images from person worn cameras (the SenseCam) (17) which provide a more direct comparison measure (9, 10).

METHODS

Participants

Participants were adults recruited through a university-based cycle-to-work network. We sampled active commuters and cyclists because we wanted a sufficient number of bicycling trips (as well as trips of other modes) to test how PALMS algorithms perform across walking/running, bicycling and vehicle trip modes. Eligible participants were university employees or students at least 18 years old who provided informed written consent. All study procedures were approved by the research ethics board of the University of California, San Diego.

Measures

Participants wore a GPS data logger and SenseCam device, which were time synchronized to the minute, during waking hours for 3–5 days, including some weekend days. We chose a 3–5 day monitoring period (vs. the conventional 7 day period for physical activity studies) because the goal was simply to yield a sufficient number of case examples rather than a stable estimate of habitual behavior.

GPS data collection and processing—Participants wore a Qstarz BT-Q1000XT GPS data logger device attached to a belt on their hip. The device recorded latitude and longitude, elevation and satellite signal data at 15-second epochs (i.e., one fix every 15 seconds when a GPS signal was attainable). The data were aggregated to the minute level in PALMS because one minute is a commonly used and meaningful timeframe (e.g., 2, 23) and provided the ability to match the GPS and SenseCam data. PALMS version 4 was used to process the GPS data, including filtering invalid GPS fixes caused by satellite interference, and identifying trips and trip mode. PALMS allows users control over parameter settings for trip detection and mode classification algorithms. The major trip-related settings were informed from empirical testing and existing algorithms (2, 6, 7, 8, 16, 21, 23, 27) and are described in detail below. Information on the other parameter settings (of less relevance to the present study) used in the scoring protocol can be obtained by contacting the first author.

Distance and speed between every sequential fix (yielding a latitude and longitude coordinate in GPS) were computed in PALMS. Groups of sequential fixes (≥ 2 minutes) were considered trips if they spanned ≥ 100 meters with an average speed of ≥ 1.5 km/hour. Pauses of up to 5 minutes were allowed during a trip to account for circumstances such as stop lights. Trips with a 90th percentile speed of ≥ 35 km/hour were classified as vehicle trips, trips with a 90th percentile speed between 10 and 35 km/hour were classified as bicycling trips, and trips with a 90th percentile speed < 9 km/hour were classified as walking/running trips. We chose ≥ 35 km/hour as the cut point for vehicle time, which is higher than the default setting, because this sample consisted of commuting cyclists who were expected to have an average cycling speed of up to approximately 35 km/hour. Thus, we aimed to minimize misclassification of bicycling as vehicle time.

Next, one PALMS parameter was manipulated in two different ways to create two unique outputs. The first output represented using PALMS with newer GPS devices (e.g., Qstarz BT-Q1000XT) that assess the signal-to-noise ratio, which suggests whether the person is indoors or outdoors. The second output represented using PALMS with older GPS devices (e.g., GlobalSat DG-100) that cannot assess the signal-to-noise ratio. For the former output, PALMS eliminated trips where > 90% of the trip was indoors (with signal-to-noise ratio ≤ 225 indicating indoors; sensitivity = 89% and specificity = 82.4% for classifying indoor time)(14). For the latter output, 100% of the trip was allowed to be indoors, which is the equivalent of not using this parameter in trip detection (mimicking use of an older device without satellite signal options). We then employed an additional algorithm to the second output, not part of PALMS, to minimize GPS scatter being classified as trips.

SenseCam data collection and processing—The SenseCam was worn on a lanyard around the neck with adhesive clothing tape attached to reduce movement. Images were captured by the device when the onboard sensors were activated (e.g. when there was a change in movement, light, temperature or presence of another person) or approximately every 20 seconds if a sensor was not triggered. The number of images taken per minute typically ranged from 3–10. The exception was that participants were allowed to use a "privacy button" on the device, which prevented the device from capturing image data for up to 7 minutes. Participants were required to charge the GPS and SenseCam device each night and received daily reminder SMS text messages for compliance.

SenseCam images were downloaded by the research staff and imported into the Clarity SenseCam Browser (4). Participants were given the opportunity to delete images they did not want to share. A standardized annotation protocol was developed to code when the participant wearing the camera was in a vehicle (y/n), bicycling (y/n), and walking/running (y/n) (see Kerr 2013 for more details)(12). Walking/running was defined as progress towards a distant point, so incidental movement would not be considered walking/running. Bicycling was coded when handlebars were present in the image. In a vehicle (could include bus) was determined by presence of a steering wheel, windscreen or car/bus seat. We also coded each image as indoors or outdoors, and focused the analyses on outdoor trips because GPS signals are not reliable in some indoor environments and thus indoor trip detection was expected to be poor (13, 26). Images were classified as uncodeable when the camera lens was obstructed or the image was indiscernible.

Inter-rater reliability of image annotation was established using an iterative cycle of blind-coding (relative to other coders) followed by discussion, with all disagreements resolved by group consensus. This yielded a set of images with criterion codes attached from which additional coders could be trained and certified. Subsequent coding was done by three research assistants who had demonstrated ≥ 80% agreement with criterion-coded images. Once certified, 10% of all subsequent images were checked to minimize observer drift. Coders also received additional training in protecting the privacy, confidentiality, and security of the images.

Analysis

Prior to data analysis, the GPS and SenseCam data files were merged and matched at the minute level. To be considered a "SenseCam" trip, the SenseCam trip codes (i.e., in vehicle, bicycling, walking/running) had to span ≥ two consecutive minutes because two minutes was the minimum trip duration set in PALMS. Minutes with only uncodable images (5.6%), no images (i.e., privacy button was on; 19.2%), or no GPS signal (17%) were removed from the dataset. Based on our experience, the privacy button is most frequently used indoors during bathroom breaks or private meetings and uncodable images are typically caused by clothing temporarily covering the camera lens. Poor GPS signals most frequently occur indoors when there is no movement to facilitate satellite connectivity (13, 26)..

For each minute of data, a variable was created to indicate whether PALMS classified the minute as part of a trip (y/n) and another variable indicated whether SenseCam classified the minute as part of a trip (y/n). Next, 2 × 2 contingency tables were used to calculate minute-level trip detection (all modes combined, excluding indoor trips) accuracy, sensitivity, specificity, positive predictive value, and negative predictive value for PALMS, using SenseCam as the comparison measure. Misclassification across modes was assessed similarly using confusion matrices. Indoor walking/running trips were investigated separately to show the validity of GPS for assessing indoor trips (rather than the validity of the PALMS algorithms for classifying indoor trips).

Lastly, because many health outcomes are related to accumulated behavior rather than each trip per se, day-level variables were created to represent minutes/day in trips and in each mode as indicated by PALMS and SenseCam. Mixed effects linear regression, adjusted for nesting of days within participants, was used to compare minutes/day as indicated by PALMS to minutes/day as indicated by SenseCam. Intraclass correlation coefficients (ICCs) were estimated using mixed effects regression to represent the association between the methods of measurement, adjusted for the nested data structure. The commonly used threshold of ICCs ≥ .80 and agreement ≥ 80% (bias ≤ 20%) was used to infer acceptable validity (e.g., 15).

RESULTS

A total of 40 participants completed the study (Mean age = 36; SD = 12). Seventy percent of participants were male, 85% were White non-Hispanic, and 33% reported an annual household income ≥ $100,000. The minute-level dataset included 72,693 minutes (1,211.55 hours) of data across an average of 4 days of device wear per participant. SenseCam coding resulted in classifying 18.2% of minutes as trips.

Trip classification for newer devices

PALMS (with parameters set for newer devices) classified 21.5% of wear time as trips (see Table 1). Accuracy from the 2 × 2 contingency tables was 92.5% and sensitivity, specificity and negative predictive value were > 85%, as compared to SenseCam. PALMS detected 88.5% of trip minutes and 93.4% of non-trip minutes captured by SenseCam. Positive predictive value was the lowest of the performance values (74.9%), meaning that PALMS was slightly prone to false positives (i.e., classifying a minute as a trip when it was not a trip).

Trip classification by mode is presented in Table 2. Agreement between PALMS and SenseCam was 76% for vehicle minutes, 73% of bicycling minutes, and 65% for walking/running minutes. PALMS misclassified 20% of bicycling minutes as in vehicle. PALMS misclassified 12% of walking/running minutes as bicycling and 19% as not a trip. Seventy-two percent of indoor walking/running was not classified by PALMS as a trip.

Table 3 presents between-methods comparisons for minutes/day in each trip mode. On average, PALMS overestimated each participant's minutes/day in vehicle by 5 minutes (17.1%), bicycling by 2.9 minutes (9.1%), and walking/running by 3.1 minutes (14.7%), as compared to SenseCam. ICCs representing between-method correlations were all > 0.80.

Trip classification for older devices

PALMS (with parameters set for older devices) classified 20.1% of wear time as trips (see Table 4). Accuracy from the 2 × 2 contingency tables was 92.7% and sensitivity, specificity and negative predictive value were > 85%, as compared to SenseCam. PALMS detected 85.2% of trip minutes and 94.4% of non-trip minutes captured by SenseCam. Similar to the finding with the newer devices, positive predictive value was the lowest of the performance values (77.1%), meaning that PALMS was slightly prone to false positives (i.e., classifying a minute as a trip when it was not a trip).

Trip classification by mode is presented in Table 5. Agreement between PALMS and SenseCam was 73% for vehicle minutes, 74% for bicycling minutes, and 57% for walking/running minutes. PALMS misclassified 20% of bicycling minutes as in vehicle. PALMS misclassified 11% of walking/running minutes as bicycling and 27% as not a trip. Eighty percent of indoor walking/running was not classified by PALMS as a trip.

Table 6 presents between-methods comparisons for minutes/day in each trip mode. On average, PALMS overestimated each participant's minutes/day in vehicle by 4.3 minutes (14.7%) and bicycling by 2.3 minutes (7.2%). PALMS underestimated minutes/day of walking/running by 2.4 minutes (11.4%), as compared to SenseCam. ICCs representing between-method correlations were all ≥ 0.80.

DISCUSSION

The present study established group-level validity for PALMS GPS trip detection and mode classification algorithms as compared to annotated SenseCam images. The PALMS algorithms performed similarly to and in some cases better than existing GPS algorithms (e.g., 2, 6, 7, 8, 23). PALMS had a minute-level accuracy (from 2 × 2 contingency table) of just under 93% for detecting trips. Minute-level sensitivity (88.5%) and specificity (93.4%) for detecting trips in PALMS were similar to widely accepted accelerometer cut points for detecting MVPA as compared to lab-based protocols and indirect calorimetry (e.g., Freedson: sensitivity = 89.9, specificity = 89.2; Evenson: sensitivity = 88.3, specificity = 91.7)(24). When looking separately by mode, validity estimates were somewhat lower due to mode misclassification. Mode-specific minute-level agreement between PALMS and SenseCam was over 70% for vehicle time and bicycling, but lower for walking/running. Importantly, minutes/day in each mode as estimated by PALMS were on average within 5 minutes of SenseCam estimates, and average bias was < 20%. ICCs representing between-method correlations were also adequately high (all ICCs ≥ .80). These findings suggest that PALMS has validity for deriving minutes/day of vehicle time, bicycling and walking/running from GPS data in population studies. This is a promising finding given the relative simplicity of wearing a GPS device.

To our knowledge, a limitation of previous studies is that none compared minutes/day in each mode between the GPS algorithms and comparison measures. Kang et al. (8) compared GPS-derived minutes/day of walking/running to travel diary-derived walking/running and found that GPS overestimated walking/running by 17.5% (slightly higher than the bias estimates in the present study), but other modes were not investigated. Minutes/day in each mode are frequently the final travel variables derived from GPS that are used in statistical analyses in health studies. For example, a researcher might investigate the association between neighborhood walkability and minute/day of walking. Thus, it is the validity of these variables that is most important in health research. PALMS performed well on these variables -- within 20% of SenseCam for all modes. Given the burden of self-reported travel diaries and the known biases of travel recall, such a magnitude of error for the GPS data is reasonable and potentially less than that of self reports (9). GPS has other benefits over self report since latitude and longitude coordinates, which can be used to derive meaningful variables such as speed and distance, are also available from GPS data.

The speed cut points used for mode classification resulted in some misclassification. Specifically, 11–12% walking/running was misclassified as bicycling (because the average trip speed was ≥ 10 km/hour), and approximately 20% bicycling was misclassified as vehicle time (because the average trip speed was > 35 km/hour). PALMS allows users to change these cut points, so the parameters can be chosen based on the characteristics of the sample to maximize validity of mode classification. For example, bicycling cut points of 10 to 25 km/hour rather than 10 to 35 km/hour may be more appropriate for children, who typically bicycle at lower speeds than adult cyclists. Researchers would be well advised to calibrate the PALMS algorithms to their population of study with a small observation period (20). Incorporating accelerometer data into mode classification algorithms, as done in some studies (8, 23), would likely improve mode classification. Preliminary research suggests that machine learning algorithms that utilize accelerometer and GPS data improve trip detection and mode classification (5). If confirmed in further studies this could add value to PALMS. Although such algorithms perform better than the more simplistic decision tree approach employed by PALMS, they require more processing power whereas PALMS is more easily available to researchers through the Internet.

We chose to test two different parameter settings in PALMS to represent using devices that can (i.e., newer devices) and cannot (i.e., older devices) assess the signal-to-noise ratio, which helps determine when the participant is indoors vs. outdoors. We expected the algorithm for newer devices to perform best because it utilized more information, but interestingly both algorithms performed similarly well. This is a promising finding because it suggests researchers can employ our scatter-minimizing algorithm to derive valid trip estimates from older GPS devices. The scatter-minimizing algorithm used bearing changes and other information from the GPS to detect "false trips" which can occur when participants are indoors and the GPS signal jumps around (i.e., due to satellite interference) in a manner mimicking a trip. This is less of a problem with newer devices because PALMS is able to exclude indoor time from trip detection.

One potential source of misclassification was that multi-mode trips (i.e., two sequential trips of different modes, for example when a participant walks to their vehicle and drives to another location) are difficult to classify. Close examination of the data revealed that, when the walking/running trip was short and vehicle trip long, PALMS sometimes missed the mode switch and classified the two trips trip as one vehicle or bicycling trip. Thus, multi-mode trips are likely one source of misclassification in PALMS, particularly for walking/running. Other studies, have only classified walking/running as trips when lasting for ≥ 5 minutes (8), so in comparison PALMS is performing well. Also, we were not able to assess the distance traveled or whether bicycles and vehicles were actually moving from the SenseCam images. This could have led to misclassification and weakened the validity estimates. Our definition of walking required the images to show that the participant was progressing towards a distant point, which is a study strength.

The three sources of missing data, uncodable SenseCam images, no SenseCam images, and loss of GPS signal, could have led to misestimation of the validity estimates. However, our experience and previous evidence suggests that this missingness is more likely to occur when participants are stationary than when traveling. Thus, the missingness likely decreased the number of true negatives (i.e., both SenseCam and PALMS classify the time as non-trip time) observed in our 2 × 2 contingency tables, resulting in underestimation of specificity and accuracy. Nonetheless, missing GPS data can impair researchers' ability to detect trips (13). While SenseCam provided a meaningful comparison measure for the present study, replicability may be difficult due to the challenges in collecting (e.g., privacy concerns) and processing (e.g., annotating images) SenseCam data. It is important to note that, while PALMS aids in processing GPS data, collecting and processing GPS data can be burdensome. Though this is improving as use of GPS becomes more common.

Implications for research and practice

Valid trip detection and mode classification with GPS has several implications for physical activity research and practice. Objectively assessing active and sedentary transportation will allow improved validity (over self-report measures) and ability (over accelerometry) for identifying correlates of specific types of physical activity (e.g., walking), particularly in the field of built environment research. Daily travel time measures, as outlined in Tables 3 and 6 of the present study, will be useful evaluation criteria in intervention studies aiming to increase active transportation and/or decrease vehicle time. In particular, GPS and accelerometer data combined can more accurately assess bicycling, whereas intensity thresholds for hip worn accelerometers alone miss cycling almost entirely (5). Bicycling may be an important behavior to support for active transportation in the U.S. as many distances are more appropriate for bicycling than for walking/running. GPS devices may also provide new insights into the relation of vehicle time to health outcomes, which is an important area of sedentary behavior research. Transportation studies, for example, are now employing GPS to understand travel behavior (1). Without systems like PALMS, data processing remains a challenge, especially aggregation with accelerometer data. The advantage of PALMS over existing algorithms is that the PALMS algorithms are incorporated into a web-based, user-friendly software that allows users control over parameter settings for their population or research question.

Conclusions

Trip detection and mode classification using PALMS processed GPS data has validity for objectively measuring time walking/running, bicycling, and in vehicle in population studies. This study also demonstrates the utility of the SenseCam to validate methods of assessing behavior in free-living individuals. The reach of using GPS to assess travel patterns is potentially high because PALMS is low cost and accessible to users via the Internet. Many aspects of the PALMS algorithms can be manipulated by users, which could improve accuracy over the present findings. Classifying trip modes is one of many valuable applications of GPS in physical activity research that can improve our understanding of the determinants and health outcomes of active transportation as well as its impact on increasing physical activity.

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Table 1

Trip classification at minute level (newer devices)

	Minutes (total percent)	
	SenseCam trip yes	**SenseCam trip no**
PALMS trip yes	11,704 (16.1%)	3,925 (5.4%)
PALMS trip no	1,527 (2.1%)	55,537 (76.4%)

PALMS Accuracy = 92.5%; Sensitivity = 88.5%; Specificity = 93.4%; Positive Predictive Value = 74.9%; Negative Predictive Value = 97.3%

Table 2

Trip mode classification at minute level (newer devices)

	Minutes (column percent)				
	SenseCam no trip	**SenseCam vehicle**	**SenseCam bicycling**	**SenseCam outdoor walking**	**SenseCam indoor walking**
PALMS no trip	54,433 (93.4%)	616 (13.3%)	236 (4.7%)	625 (18.7%)	1022 (71.5%)
PALMS vehicle	1,016 (1.7%)	3,513 (76.0%)	1,002 (20.0%)	143 (4.3%)	46 (3.2%)
PALMS bicycling	1,312 (2.3%)	300 (6.5%)	3,655 (73.1%)	392 (11.7%)	68 (4.7%)
PALMS walking	1,526 (2.6%)	195 (4.2%)	111 (2.2%)	2,187 (65.3%)	295 (20.6%)

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Table 3

Mean difference and agreement for minutes per day in trips (newer devices; N = 155 days)

	Estimated Mean (SE) Minutes/day[a]				ICC (95% CI)[a]
	SenseCam	**PALMS**	**Difference (PALMS - SenseCam)**	**p**	
All trips	82.2 (6.8)	93.4 (6.8)	11.2 (2.3)	< .001	.91 (.85, .94)
Vehicle trips	29.3 (4.5)	34.3 (4.5)	5.0 (1.9)	.010	.85 (.79, .89)
Bicycling trips	32.0 (3.7)	34.9 (3.7)	2.9 (1.8)	.104	.81 (.75, .86)
Walking trips (outdoor)	21.2 (2.9)	24.3 (2.9)	3.1 (1.3)	.016	.85 (.80, .89)

[a]From mixed-effects linear regression models adjusted for nesting of days within participants

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Table 4

Trip classification at minute level (older devices)

	Minutes (total percent)	
	SenseCam trip yes	**SenseCam trip no**
PALMS trip yes	11,278 (15.5%)	3,348 (4.6%)
PALMS trip no	1,952 (2.7%)	56,115 (77.2%)

PALMS Accuracy = 92.7%; Sensitivity = 85.2%; Specificity = 94.4%; Positive Predictive Value = 77.1%; Negative Predictive Value = 96.6%

Table 5

Mode classification at minute level (older devices)

	Minutes (column percent)				
	SenseCam trip no	**SenseCam trip vehicle**	**SenseCam trip bicycling**	**SenseCam trip outdoor walking**	**SenseCam trip indoor walking**
PALMS no trip	55,012 (94.4%)	778 (16.8%)	241 (4.8%)	917 (27.4%)	1,150 (80.4%)
PALMS vehicle	1007 (1.7%)	3,437 (74.4%)	998 (19.9%)	137 (4.1%)	69 (4.8%)
PALMS bicycling	1,320 (2.3%)	240 (5.2%)	3,661 (73.2%)	374 (11.2%)	35 (2.4%)
PALMS walking	949 (1.6%)	169 (3.6%)	104 (2.1%)	1,920 (57.4%)	177 (12.4%)

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Table 6

Mean difference and agreement for minutes per day in trips (older devices; N = 155 days)

	Estimated Mean (SE) Minutes/day[a]				ICC (95% CI)[a]
	SenseCam	**PALMS**	**Difference (PALMS - SenseCam)**	**p**	
All trips	81.9 (6.7)	86.0 (6.7)	4.1 (2.3)	.069	.90 (.87, .93)
Vehicle trips	29.2 (4.4)	33.5 (4.4)	4.3 (1.9)	.023	.85 (.80, .89)
Bicycling trips	31.9 (3.7)	34.2 (3.7)	2.3 (1.9)	.221	.80 (.74, .85)
Walking trips (outdoor)	21.0 (2.6)	18.6 (2.6)	−2.4 (1.1)	.036	.88 (.83, .91)

[a] From mixed-effects linear regression models adjusted for nesting of days within participants