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Integration of accelerometers, global positioning systems (GPS) and geographical information systems (GIS) for measuring physical activity

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Abstract

We tested the feasibility of integrating Actigraph accelerometers (AG), Global Positioning Systems (GPS) and Geographical Information Systems (GIS) to explore the physical activity in 26 healthy adults and 7 post-stroke individuals. The study subjects wore AG and GPS devices for 7 days. Feasibility outcomes were participants' experience of using these devices and data quality regarding i) valid and synchronized data between the AG and GPS; ii) GPS data distribution among participants living in areas characterized by differently developed built environments; and iii) time and intensity of physical activity in and outside the home. There were >10 hours of synchronized data between the devices and the majority (94%) of participants, irrespective of group, did not report any problems using the AG or GPS. Individuals living in low-density built environment had a higher percentage of GPS points closer to the home compared to those living in areas with high-density built environment where GPS scattering occurred. Although methodological challenges regarding scattering and GPS signal loss in densely built environment in urban areas, the results support the overall feasibility of integrating AG, GPS and GIS to investigate physical activity behaviour.

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Availability of data and materials: the data cannot be made publicly available due to ethical and legal reasons (*i.e.*, public availability would compromise patient privacy). However, the data supporting the findings of this study are available upon request from the Research Data Office at Karolinska Institute (rdo@ki.se).

Ethics approval: the study was approved by the Swedish Ethical Review Authority (https://etikprovningsmyndigheten.se/en/) (2017/1626-31 and 2018/2524-32) and all participants gave written informed consent before participation.

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Introduction

Existing literature has shown that social and economic factors (Rodriguez *et al.*, 2005) and physical abilities are associated with physical activity among the general population and people living with disability (Ellis *et al.*, 2013; Gunnes *et al.*, 2019). Excessive time spent sedentary is associated with an increased risk of death, even in healthy adults (Ekelund *et al.*, 2019), and people with impaired mobility, *e.g.,* post-stroke individuals, spend more sedentary time compared to healthy adults (English *et al.*, 2016). It is recognized that the features of built environment (e.g., home, residential neighbourhoods and work) could act as barriers or facilitators to physical activity (Troped *et al.*, 2001; Rodriguez *et al.*, 2005; McNeill *et al.*, 2006). Although accelerometers have evolved as a preferred method to measure physical activity (Bernmark & Wiktorin, 2002, Chen *et al.*, 2003, Leuenberger *et al.*, 2017; Lonini *et al.*, 2018; Silfee *et al.*, 2018), understanding how physical activity relates to the spatial environment remains limited in clinical populations. While numerous studies have combined accelerometers with GPS to explore activity patterns in the general population (Marquet *et al.*, 2022), there is a lack of research applying these methods in post-stroke individuals. To better comprehend environmental barriers in relation to various groups of people, *e.g.*, individuals with stroke symptoms and assist target interventions (Maddison *et al.*, 2010), it is not only important to identify how much activity occurs, but also where it takes place.

Global Positioning Systems (GPS) devices utilize trilateration between three or more GPS satellites to determine the receiver's position, speed and elevation. GPS has been extensively used for commercial applications over the last decades (*e.g.*, navigation and land surveying) and for research (*e.g.*, human movement and sports sciences) (Schutz & Chambaz 1997; Rodriguez *et al.*, 2005; Maddison & Ni Mhurchu, 2009). Technological advances over the last decade have made it possible to measure and store GPS data for prolonged periods. However, GPS signal accuracy is known to be reduced when the device is recording indoors or in highly dense urban areas (especially among tall buildings) and under tree canopies due to signal obstruction and multipath effects. Buildings and tree canopies act as barriers for the GPS signal that could lead to gaps or inaccuracy in the GPS recordings (Schutz & Chambaz, 1997; Webber & Porter, 2009; Maddison *et al.*, 2010).

The combination of GPS and accelerometry has been used as a tool to measure physical activity for two decades, with an early landmark study by Rodriguez *et al.* (2005) demonstrating the potential of this method to capture both physical activity and spatial context. More recently, Rosli *et al.* (2013) tested the use of a GPS and an accelerometer to graphically map physical activity levels among 10 university students over two different jogging courses for 90 minutes. Their results suggest that the two devices are feasible for the objective measuring of physical activity (Rosli *et al.*, 2013). For daily living, Maddison *et al*. (2010) presented the first study to describe the location and intensity of physical activity in adolescents using GPS, accelerometry and Geographical Information Systems (GIS). The latter is a spatial database containing geographical data that can be analyzed, managed and visualized. When combined with the accelerometer and GPS data, the GIS information gives context to where (e.g., home, work, park, etc.) the physical activity was conducted. Marquet *et al.* (2022) recorded GPS and accelerometer data from 354 working adults across the United States for one week showing that higher activity spatial walkability correlated with higher levels of Moderate to Vigorous Physical Activity (MVPA), while higher spatial greenness was linked to increased weekly step counts (Ahlstrom *et al.*, 2015). To our knowledge, no previous study has combined accelerometry and GPS to examine physical activity in post-stroke individuals. This combined method offers a more detailed understanding, both of the amount and the location of physical activity, providing valuable insight into community mobility patterns, environmental context and levels of social participation. Community engagement is a critical component of post-stroke recovery and is closely linked to improved quality of life (Elayoubi *et al.*, 2023). Capturing the spatial context of physical activity can help identify environmental and behavioural barriers to participation, thereby supporting the development of more targeted and effective rehabilitation strategies. GPS and accelerometry are well-known ways to measure physical activity, However, to the best of our knowledge, no study has tested the feasibility of integrating accelerometers, GPS and GIS systems in adults of different age groups and in people living with post-stroke symptoms and other disabilities. Post-stroke individuals and older adults could have different barriers to using and managing multiple devices (*e.g.*, difficulty in wearing, operating or charging devices) for the assessment of physical activity. This study, therefore, aimed to explore the feasibility of integrating accelerometers, GPS and GIS to explore physical activity in daily living. Our specific aims were to i) investigate the study participants' experience and acceptance of using the GPS and accelerometers; ii) explore the quality of data (*i.e.* degree of valid and synchronized data between the accelerometer and GPS recordings) and GPS data distribution among participants living in differently developed areas; and iii) preliminary explore and compare time and intensity of physical activity in the home and in the outside environment.

Materials and Methods

Study participants

Twenty-six healthy, adults of different ages and 7 post-stroke individuals participated in this feasibility study. People who suffered a stroke ≥3 months prior to study participation, with the ability to ambulate with/without a walking device were recruited from rehabilitation centres and through advertisements. Exclusion criteria included cognitive deficit, severe neglect and aphasia that affected the ability to give written consent and follow instructions. Healthy, community-dwelling, individuals recruited through advertisement were included if able to ambulate independently over short distances with/without a walking device. The study was approved by the Swedish Ethical Review Authority (https://etikprovningsmyndigheten.se/en/) (2017/1626-31 and 2018/2524-32) and all participants gave written informed consent before participation.

Data collection

All participants attended one session which included a collection of demographic data (sex, age, lifestyle), employment status and mobility status by using a structured interview. Subsequently, the participants were equipped with one accelerometer (Actigraph GT3X+; AG) and a GPS (QStarz BT-Q1000XT) for the measurement of physical activity in daily life. The AG and GPS sensors are lightweight (<20 grams each) and could be attached around the right hip using an elastic belt. The GPS device was set to record at a sample rate of 15 seconds and the AG at 30Hz. Data collection occurred during autumn and winter seasons of from September 2020 to April 2021, which incidentally coincided with the Covid-19 pandemic in Sweden.

Each participant was asked to wear the devices for 7 consecutive days during all hours when awake and to make note using an activity diary of the times when the devices were worn. The participants were also asked to charge the GPS device each night before going to sleep. The AG device was initialized by the study coordinator to start recording before the measurement of each participant, while the GPS device needed to be initialized by the participants themselves the first time used. This was done by standing outside, switching the device on and waiting for a few seconds (up to a minute) for the GPS to acquire signals from the satellites at which time a LED light turned on indicating that the device had been initialized. This meant that the GPS clock was synchronized with the satellite atomic clock (Schutz and Chambaz 1997, Maddison and Ni Mhurchu 2009). The AG device utilizes the local computer time to initialize the device timestamps. To synchronize the AG and GPS devices, the local computer time was reset to coordinated universal time (UTC) using the built-in Windows tool for each AG device before initialization. UTC is the primary time standard at which most countries regulate their timestamps and is based on the international atomic time (Panfilo & Arias, 2019). After the measurement period, the participants returned the devices to the research coordinator using a pre-paid mail service.

Wearing the measuring devices

The study participants' experience and acceptance of wearing and managing the accelerometer and GPS were assessed through a telephone interview after the measurement period. The interview included questions whether the participant had experienced any problems using the devices in daily life (yes/no), if wearing the devices affected normal daily activities (yes/no) and if the participant had changed daily activities during the measurement period (yes/no). If any participants encountered problems with the measurement or changed daily activities during measurement, they were asked to describe the problems experienced or how they have changed their activities (open-ended questions). They were also asked to rate (1 = not satisfied to 3 = very satisfied) if they perceived the oral and written information about how to manage the devices as understandable and relevant.

Data quality

The data from the healthy adults were divided into two age groups: ≤45 and >45 years old. This cut-off was selected to achieve a more balanced distribution of participants across age groups to enhance comparability between the groups. Demographic data were presented for each group as mean, median and ranges. Proxies for data quality were the number of recorded days, AG wearing time (min), time-frame of the GPS device recorded data and the synchronized wearing time between the two devices. The raw AG physical activity data were converted into 15-second periods and exported to Excel using the Actilife 6 software, v. 6.13.4 (https://theactigraph.com/actilife). The 15-second period data were divided into daily segments and a non-wearing time algorithm as done by Choi *et al.* (2011) taking into account 90 minutes of consecutive zero counts and 2 minutes of non-zero counts with an upstream/downstream period of 30 minutes of consecutive zero counts. The periods of non-wearing time were also confirmed by the participant's activity diaries. The median daily wearing time (minutes) of recordings with the AG over the 7 study days were calculated. A day was considered valid if there were ≥10 hours of collected AG data (Migueles *et al.*, 2017). To obtain the wearing time of the GPS device, GPS data (*i.e.* date, time, latitude and longitude) were first exported to Excel using the Qstarz travel software (http://www.qstarz.com/), divided into daily data and the median daily wearing time (minutes) calculated. Subsequently, the changing geographical coordinate information and its corresponding time stamps were synchronized with the AG data using the date and time stamps. The number of minutes per day with synchronized AG and GPS data was calculated as a proxy of data quality. It is worth noting that AG wearing time represents the time when the participants wore the device whereas one could expect a lower wearing time for the GPS due to blockage of the GPS signal (e.g., during time spent in dense areas). Subsequently, the Kruskal-Wallis test was used to compare the wearing of the two devices, the synchronized time and the time spent at home and outside across the study groups followed by *post hoc* analysis by the Mann-Whitney U tests with the Bonferroni corrections added to adjust the *p*-values. For the assessment of GPS data distribution as a function of spatially developed areas, the GPS data were projected into the Swedish national coordinate system (SWEREF 99 TM) (Kempe *et al.*, 2010). GPS data points were classified within buffers of varying radius from the Points Of Interest (POI), *i.e.* the home address of each participant. Buffers were set at 20, 50, 100 and 150 m. For assessment of the building densities, building polygons were extracted from OpenStreetMap (2015) for the entire study area. Building densities were calculated within each 150 m radius from the POI, which equated to a total included area of 70,685 m^2. Subsequently, participants were divided, based on their associated POIs, into groups, wither with low-density built environment (≤15% of the total area included 70685 m^2) or one with a high-density built environment (>15% of the total area). The mean percentage points and standard deviation (SD) for each buffer were calculated for all study participants with respect to building density and compared using the Mann-Whitney U-test.

Preliminary exploration of physical activity

The physical activity focused on exploring the time and intensities of physical activity performed in the participant's home and outside this environment. The approach rationale here was based on the previous observation that most people spend the majority of their time indoors (Velux, 2018) in sedentary states (Matthews *et al.*, 2008). A search radius of 100 m was assigned to each POI to distinguish between the time spent at home and the time spent outside. Furthermore, the daily 15-second period of physical activity inside and outside the home were determined after division into sedentary, light intensity physical activity (LIPA) and MVPA (Freedson *et al.*, 1998; Matthews *et al.*, 2008; Troiano *et al.*, 2008) and the average time spent at each intensity level per day over the 7 study days.

Results

Participant characteristics

The demography of the 26 healthy participants and 7 post-stroke individuals participating in this study is shown in Table 1. The median age of the post-stroke participants was higher (63 years) than the healthy group (40 years). Most post-stroke individuals used a walking aid (57%), lived in a house (71%) and were retired (57%), while most of the healthy participants reported working full time (range: 71-92%) with most of the participants ≤45 years old living in an apartment (86%) compared to the participants >45 years old (42%) and post-stroke individuals (29%).

Experience and acceptance of using the measuring devices

None of the study participants felt that wearing the AG and GPS devices restricted their everyday activities. During the measurement period most of the participants ≤45 years of age (64%) reported that they deviated from their normal weekly routines as compared to 10% of the participants >45 years of age and 20% of those living with post-stroke symptoms. All participants considered the oral and written instructions/information easy to understand, relevant and sufficient.

Data quality

Table 2 details the summary of the AG and GPS data. Twenty-four of the 26 adults (92%) and all post-stroke individuals wore the devices for the entire measurement period (7 days). Two healthy ≤45 years old participants were excluded from the analysis since they did not have sufficient AG and GPS data for at least 4 days. The median wearing time for all groups was ≥935 minutes (close to 16 hours) of recorded daily AG data and >64% of the AG wearing time was synchronized AG and GPS data. Participants aged >45 years had statistically significantly higher AG wear time than the post-stroke group and longer synchronized AG-GPS wearing time than the group aged <45 years. No significant differences between the groups were found for GPS wearing time or time spent in or outside the home. Of the 31 participants, 15 lived in areas with low-density built environment and 16 in areas of opposite configuration. Table 3 shows the mean (SD) percentage number of points within each buffer of varying radius from the POI (*i.e.,* the home) for individuals living in low-density built areas and those living in high-density environments. On average, the percentage number of points in the 20-m radius for the individuals living in low-density areas was 80% (SD: 3%) compared to 70% (SD: 12%) of those living in high-density areas. There was also a statistically significant difference between all the mean percentage GPS points within the areas of both low-density and high-density built environment for the different buffer radii (*i.e.,* 20-150 m). Figure 1A-B shows anonymous representative data of GPS distribution for the lowly and the highly developed areas. Individuals in relatively underdeveloped areas (Figure 1B) exhibit GPS data distributed in relative proximity to their home environment, compared to individuals living in relatively high-density built environments (Figure 1A), where the GPS data are more widely scattered. The GPS data also showed that post-stroke individuals spent a median of 521 min of their recorded day at home compared to participants ≤45 years old (352 min) and >45 years old (410 min) (see Table 2).

Table 1. Demographic data.

Participant characteristic	Healthy (n=26)		Post stroke (n=7)
Age	18- 45 years of age n=14 (42.4%)	> 45 years of age n=12 (36.4%)	50-74 years n=7 (21.2%)
Personal			
Male sex, n (%)	8 (57)	5 (42)	3 (43)
Age (years), median, min-max	32 (22-43)	60 (50-68)	63 (50-74)
Living alone, n (%)	5 (36)	1 (8)	4 (57)
Accommodation type, n (%)			
House	2 (14)	7 (58)	5 (71)
Apartment	12 (86)	5 (42)	2 (29)
Employment status, n (%)			
Working	10 (71)	11 (92)	2 (29)
Retired	0 (0)	1 (8)	4 (57)
Student	4 (29)	0 (0)	0 (0)
Sick leave	0 (0)	0 (0)	1 (14)
Mobility status, n (%)			
Unaided	14 (100)	12 (100)	3 (43)
Walking aid	0 (0)	0 (0)	4 (57)

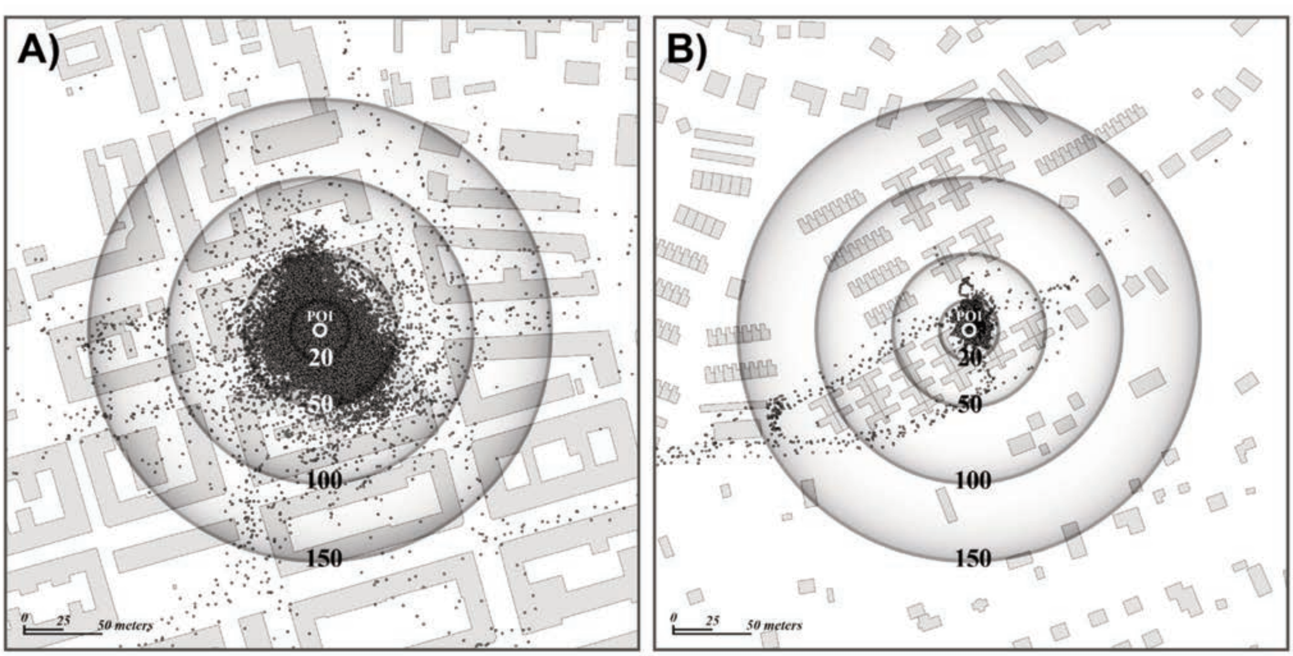

Figure 1. GPS data distribution with respect to different buffer radius overlaid with the building area density (building footprint). **A**) Example of a participant living in an area with high building density; **B**) Example of a participant living in an area with low building density.

Preliminary exploration of physical activity at home and outside

Figure 2A-B shows minutes per day and percentage of time spent in the different states (sedentary, LIPA or MVPA) at home and outside this environment for the three groups. Within the home environment, all three groups spent >74% of their recorded time sedentary with the participants ≤45 years spending between 13-15% of recorded time in LIPA (Figure 2B) compared to 8% of the post-stroke individuals. The latter group was also found to spend 8 min (2%) on average of their recorded time in MVPA per day in the home environment. Outside home, post-stroke individuals as well as the healthy adults, spent approximately the same time (14-20%) of their recorded day in LIPA with post-stroke individuals spending only 7% of their recorded time in MVPA.

Table 2. Wearing time data from AG and GPS devices.

Variable	Group: Age: 18-45 years (n=12*)	Group: Age >45 years (n=12)	Group: Post-stroke individuals (n=7)	Kruskal Wallis test	Post hoc analysis by Mann-Whitney U test with Bonferroni correction (p): Age: 18-45 years *vs* >45 years	Age: 18-45 years *vs* post-stroke	Age: >45 years *vs* post-stroke
Wearing time							
AG wearing time, median (Q_1–Q_3)	965 (883-998)	1,037 (1,012-1,047)	935 (905-940)	0.002	0.059	0.332	0.001
GPS wearing time, median (Q_1–Q_3)	1,088 (883-1,301)	1,355 (1,154-1,386)	1,250 (1,211-1,302)	0.158	0.171	0.967	1.00
Synchronized, median (Q_1–Q_3)	616 (491-757)	816 (717-872)	754 (727-793)	0.047	0.043	0.640	1.00
Time spent at home							
Minutes, median (Q_1–Q_3)	352 (171-522)	410 (300-591)	521 (342-643)	0.421	1.00	1.00	0.581
Time spent outside the home							
Minutes, median (Q_1–Q_3)	249 (147-371)	348 (231-469)	294 (120-331)	0.386	0.651	1.00	0.834

AG, Actigraph; GPS, Geographical Positional Systems; Q_1, first quartile; Q_3, third quartile: *Two healthy participants ≤45 years were excluded from the analysis after the start of the study.

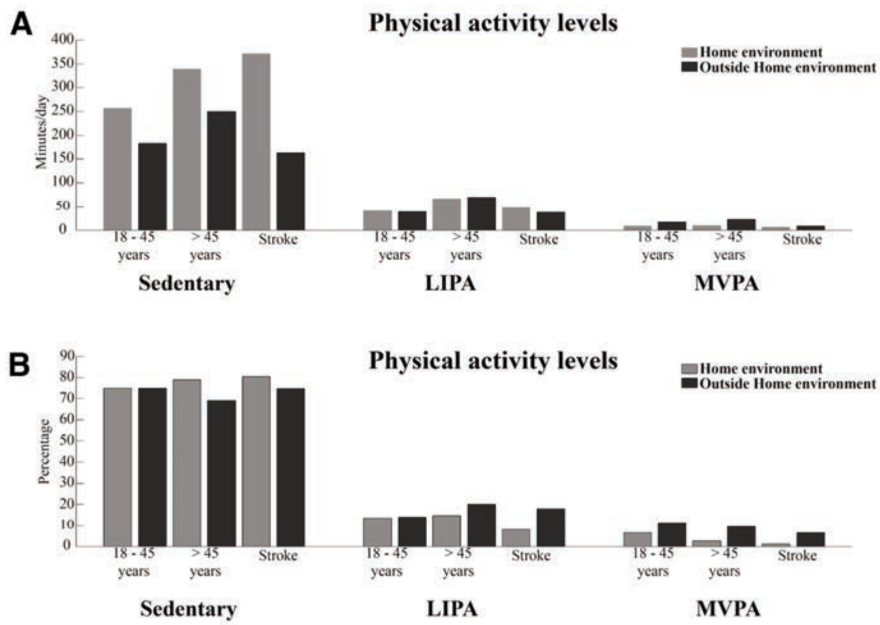

Figure 2. Mean daily physical activity levels distribution at home and outside for healthy young adults aged 18-45 years, >45 years olds and individuals with post-stroke symptoms. **A**) minutes per day; **B**) Percentage of total synchronized wearing time; LIPA, light intensity physical activity; MVPA, moderate to vigorous physical activity.

Discussion

As far as we know, this study is the first to explore the feasibility of integrating accelerometers, GPS and GIS to measure physical activity in healthy adults in different age groups and post-stroke individuals. The present results support the feasibility of an integrated approach with regard to user experience, device management and data quality.

Although our study showed that the augmentation of AG and GPS could be used to gain additional information about the spatial aspects of physical activity, using the two devices is not without potential limitations. One of the most commonly reported ones is that the use of two separated devices results in participant inconvenience, e.g., the weight of two devices on one side of the waist for an entire day as pointed out by Maddison *et al.* (2010). Although some individuals, especially older adults and post-stroke individuals, could be expected to have problems wearing two devices around the waist over a day, none of the participants in our study reported having problems of this kind. We purposively recruited persons in different age groups and post-stroke individuals as old age and physical disability are potential barriers to using and managing multiple devices (*e.g.*, difficulty operating or charging them) for assessment of physical activity. Previous studies have mainly focused on the feasibility of using accelerometers and GPS devices in older adults during shorter periods, such as just one day (Webber & Porter, 2009). Our results are consistent with these studies, supporting the feasibility of the user experience and management of this integrated approach. In a similar approach to ours, Rodriguez *et al.* (2005) piloted the use of GPS and AG in 35 healthy adults over 3 days to classify physical activity data into MVPA and match it with GPS data, *i.e.*, indoors, outdoors in the close neighbourhood, and further away. In contrast to our study, they found that about one-third of the participants had incomplete GPS data due to not adhering to the GPS protocol, malfunctioning GPS units or lack of GPS data (Rodriquez *et al.*, 2005).

While accelerometer data have proven reliable (Bernmark & Wiktorin, 2002, Chen *et al.*, 2003; Leuenberger *et al.*, 2017; Lonini *et al.*, 2018; Silfee *et al.*, 2018), there are some issues with GPS measurement, such as poor accuracy attributed to recording indoors or in highly dense urban areas and under tree canopies (Schutz & Chambaz, 1997; Maddison *et al.*, 2010). For example, a study by Webber and Porter (2009) recorded more than 8 hours of GPS data between start and final data collection points in only 55% of their 20 older adults. In line with this, our results show that the accuracy in the GPS recording distribution is higher in areas with low-density built environments compared to the opposite situation, *i.e.*, there seems to be different recipient results in rural vs. urban areas. Despite the issues surrounding the reliability of GPS devices, with respect to relevant contextual information regarding the environment (*e.g.*, home, work, parks, etc.) in which the physical activity takes place, the signals are still attainable and the approach useful. In the present study, we recorded >10 hours of syncronized AG and GPS data for all three groups, which is in line with a systematic review from Migueles *et al.* (2017) that established a valid day as >10 hours of data collected during a day.

Some of the techniques used to negate the potential errors in indoor GPS logging would be to add a buffer zone to specified areas. Maddison *et al.* (2010) described the intensity of physical activity and location in adolescents using GPS and AG in daily living. To classify the home environment they created a 150 m circular radius around each participant's home and found that from the available GPS data, the 79 adolescents in their study spent a combined total of 268 hours per day within 150 m of their homes. In our study, we used a circular radius of 100 m to delineate the participants' home environments finding that >56% of the recorded time was spent there. The discrepancy in our study compared to that used by Maddison *et al.* (2010) was the fact that we considered 150 m to be an overestimation of the home environment and therefore used a 100-m circular radius. Although the populations studied in our study and that by Maddison *et al.* (2010) were different, our physical activity levels were similar to theirs, i.e. adolescents of a mean age of 14.5 spending 70%, 13%, 15% and 1% of their recorded time at home in sedentary, light, moderate and vigorous intensities, respectively.

The results show that the physical activity outside the home environment of all the study subjects were below the recommended guidelines by the World Health Organisation (WHO) for physical activity (WHO, 2020). It is therefore worth noting that this study was conducted during the fall and winter seasons and the Covid 19 pandemic which may have contributed to the amount of time spent in the home environment and sedentary, especially among older adults and people post-stroke individuals classified as a riskgroups with regard to the pandemic.

Although Jankowska *et al.* (2015) provided a framework for using GPS data in physical activity and sedentary behaviour studies, it is still unclear as to what is the best way to present and interpret individual augmented AG, GPS and GIS data. Therefore, future work should include exploration of different techniques on a participant and group level with regard to data presentation and anonymization. In future studies with a larger sample, we plan to conduct stratified analyses and examine neighbourhood characteristics (*i.e.* activity spaces) in relation to physical activity levels for different groups to better understand the relationship between the environment and physical activity.

Limitations

Our study has some limitations which include a relatively small sample size and that most of the participants lived in the Stockholm area; therefore, the results cannot be generalizable to

Table 3. Comparison of the percentage points within each buffer radius with respect to building density.

Capsule of varying radius (m)	Low-density building area, n= 15 mean (SD)	High-density building area, n=16 mean (SD)	p
20	79.9 (2.9)	69.8 (11.8)	<0.001
50	14.7 (1.9)	20.7 (7.0)	<0.001
100	3.6 (0.6)	6.4 (3.7)	<0.001
150	1.7 (0.5)	3.1 (2.0)	0.004

SD, standard deviation.

include individuals living in rural areas. It is also worth noting that data collection was conducted during the COVID-19 pandemic, therefore the results are not a true reflection of the physical activity of the different study groups due to the various restrictions and recommendations limiting movement during the pandemic. Additionally, this study combined data from healthy and post-stroke participants, which limits group-specific interpretations. Finally, the use of GPS and GIS data creates a threat to participant privacy and requires robust ethical boundaries. One way to preserve privacy is to apply masking procedures to the GPS and GIS data. In our study, we used the true location of the home environment (*i.e.*, the postal addresses) to determine the physical activity of the participants. However, the data were anonymized with no location data presented here. The present study also highlights problems with scattering and loss of GPS data in highly dense urban areas and future work should entail developing strategies on how to address these limitations.

Conclusions

This study supports the feasibility of integrating accelerometry, GPS and GIS to investigate physical activity in relation to where, when and how healthy adults and post-stroke individuals are physically active or inactive. The physical activity levels were well below established recommendations which was expected due to the ongoing pandemic movement restricts. On the other hand, this finding strengthens the belief of the usefulness of the this integrated approach as it not only gave insights into physical activity promotion in different age groups and people living with disability but also reflected general restrictions. The present study also highlighted some challenges, more noticeably the scattering and loss of GPS data in different geographical regions. The creation of new strategies are needed to better classify missing data gaps and scattering leading to more synchronized AG and GPS data.

References

Ahlstrom I, Hellstrom K, Emtner M, Anens E, 2015. Reliability of the Swedish version of the Exercise Self-Efficacy Scale (S-ESES): a test-retest study in adults with neurological disease. Physiother Theory Pract 31:194-9.

Bernmark E, Wiktorin C, 2002. A triaxial accelerometer for measuring arm movements. Appl Ergon 33:541-7.

Chen KY, Acra SA, Majchrzak K, Donahue CL, Baker L, Clemens L, Sun M, Buchowski MS, 2003. Predicting energy expenditure of physical activity using hip- and wrist-worn accelerometers. Diabetes Technol Ther 5:1023-33.

Choi L, Liu Z, Matthews CE, Buchowski MS, 2011. Validation of accelerometer wear and nonwear time classification algorithm. Med Sci Sports Exerc 43:357-64.

Ekelund U, Tarp J, Steene-Johannessen J, Hansen BH, Jefferis B, Fagerland MW, Whincup P, Diaz KM, Hooker SP, Chernofsky A, Larson MG, Spartano N, Vasan RS, Dohrn IM, Hagstromer M, Edwardson C, Yates T, Shiroma E, Anderssen SA, Lee IM, 2019. Dose-response associations between accelerometry measured physical activity and sedentary time and all cause mortality: systematic review and harmonised meta-analysis. BMJ 366:l4570.

Elayoubi J, Haley WE, Nelson ME, Hueluer G, 2023. How social connection and engagement relate to functional limitations and depressive symptoms outcomes after stroke. Stroke 54:1830-38.

Ellis T, Boudreau JK, DeAngelis TR, Brown LE, Cavanaugh JT, Earhart GM, Ford MP, Foreman KB, Dibble LE, 2013. Barriers to exercise in people with Parkinson disease. Phys Ther 93:628-36.

English C, Healy GN, Coates A, Lewis L, Olds T, Bernhardt J, 2016. Sitting and activity time in people with stroke. Phys Ther 96:193-201.

Freedson PS, Melanson E, Sirard J, 1998. Calibration of the Computer Science and Applications, Inc. accelerometer. Med Sci Sports Exerc 30:777-81.

Gunnes M, Indredavik B, Langhammer B, Lydersen S, Ihle-Hansen H, Dahl AE, Askim T, LAST Study Group, 2019. Associations Between Adherence to the Physical Activity and Exercise Program Applied in the LAST Study and Functional Recovery After Stroke. Arch Phys Med Rehabil 100:2251-59.

Jankowska MM, Schipperijn J, Kerr J, 2015. A framework for using GPS data in physical activity and sedentary behavior studies. Exerc Sport Sci Rev 43:48-56.

Kempe T, Alfredsson A, Andersson B, Engberg L, Dahlstöm F, Lohasz G, 2010. the process of changing from local systems into SWEREF 99 – a challenge for Lantmäteriet and a great step for the municipalities. Available from: https://www.lantmateriet.se/globalassets/kartor-och-geografisk-information/gps-och-geodetisk-matning/publikationer/euref2010_paper_kempe_etal.pdf

Leuenberger K, Gonzenbach R, Wachter S, Luft A, Gassert R, 2017. A method to qualitatively assess arm use in stroke survivors in the home environment. Med Biol Eng Comput 55:141-50.

Lonini L, Dai A, Shawen N, Simuni T, Poon C, Shimanovich L, Daeschler M, Ghaffari R, Rogers JA, Jayaraman A, 2018. Wearable sensors for Parkinson's disease: which data are worth collecting for training symptom detection models. NPJ Digit Med 1:64.

Maddison R, Jiang Y, Vander Hoorn S, Exeter D, Ni Mhurchu C, Dorey E, 2010. Describing patterns of physical activity in adolescents using global positioning systems and accelerometry. Pediatr Exerc Sci 22:392-407.

Maddison R, Ni Mhurchu C, 2009. Global positioning system: a new opportunity in physical activity measurement. Int J Behav Nutr Phys Act 6:73.

Marquet O, Hirsch JA, Kerr J, Jankowska MM, Mitchell J, Hart JE, Laden F, Hipp JA, James P, 2022. GPS-based activity space exposure to greenness and walkability is associated with increased accelerometer-based physical activity. Environ Int 165:107317.

Matthews CE, Chen KY, Freedson PS, Buchowski MS, Beech BM, Pate RR, Troiano RP, 2008. Amount of time spent in sedentary behaviors in the United States, 2003-2004. Am J Epidemiol 167:875-81.

McNeill LH, Kreuter MW, Subramanian SV, 2006. Social environment and physical activity: a review of concepts and evidence. Soc Sci Med 63:1011-22.

Migueles JH, Cadenas-Sanchez C, Ekelund U, Delisle Nystrom C, Mora-Gonzalez J, Lof M, Labayen I, Ruiz JR, Ortega FB, 2017. Accelerometer data collection and processing criteria to assess physical activity and other outcomes: a systematic

review and practical considerations. Sports Med 47:1821-45.
OpenStreetMap, 2015. Planet OSM. Available from: https://planet.openstreetmap.org/
Panfilo G, Arias F, 2019. The Coordinated Universal Time (UTC). Metrologia 56(4).
Rodriguez DA, Brown AL, Troped PJ, 2005. Portable global positioning units to complement accelerometry-based physical activity monitors. Med Sci Sports Exerc 37:S572-81.
Rosli MH, Baharuldin MTH, Abdullah MNH, Fauzee MSO, Adam Y, Yaacob A, 2013. Coupling GPS with Accelerometer to Measure Physical Activity. Psu-Usm Int Conf Humanit Soc Sci 91:171-8.
Schutz Y, Chambaz A, 1997. Could a satellite-based navigation system (GPS) be used to assess the physical activity of individuals on earth? Eur J Clin Nutr 51:338-9.
Silfee VJ, Haughton CF, Jake-Schoffman DE, Lopez-Cepero A, May CN, Sreedhara M, Rosal MC, Lemon SC, 2018. Objective measurement of physical activity outcomes in lifestyle interventions among adults: A systematic review. Prev Med Rep 11:74-80.
Troiano RP, Berrigan D, Dodd KW, Masse LC, Tilert T, McDowell M, 2008. Physical activity in the United States measured by accelerometer. Med Sci Sports Exerc 40:181-88.
Troped PJ, Saunders RP, Pate RR, Reininger B, Ureda JR, Thompson SJ, 2001. Associations between self-reported and objective physical environmental factors and use of a community rail-trail. Prev Med 32:191-200.
Velux, 2018. Modern indoor living can be bad for your health: New YouGov survey for VELUX sheds light on risks of the “Indoor Generation.” Available from: https://www.prnewswire.com/news-releases/modern-indoor-living-can-be-bad-for-your-health-new-yougov-survey-for-velux-sheds-light-on-risks-of-the-indoor-generation-300648499.html
Webber SC, Porter MM, 2009. Monitoring mobility in older adults using global positioning system (GPS) watches and accelerometers: a feasibility study. J Aging Phys Act 17:455-67.
WHO, 2020. WHO Guidelines on physical activity and sedentary behaviour. Available from: https://apps.who.int/iris/ bitstream/handle/10665/336656/9789240015128-eng.pdf?sequence=1&isAllowed=y.