Identifying factors associated with sedentary time after stroke. Secondary analysis of pooled data from nine primary studies.


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Identifying factors associated with sedentary time after stroke. Secondary analysis of pooled data from nine primary studies.


**ABSTRACT**

**Background:** High levels of sedentary time increases the risk of cardiovascular disease, including recurrent stroke.

**Objective:** This study aimed to identify factors associated with high sedentary time in community-dwelling people with stroke.

**Methods:** For this data pooling study, authors of published and ongoing trials that collected sedentary time data, using the activPAL monitor, in community-dwelling people with stroke were invited to contribute their raw data. The data was reprocessed, algorithms were created to identify sleep-wake time and determine the percentage of waking hours spent sedentary. We explored demographic and stroke-related factors associated with total sedentary time and time in uninterrupted sedentary bouts using unique, both univariable and multivariable, regression analyses.

**Results:** The 274 included participants were from Australia, Canada, and the United Kingdom, and spent, on average, 69% (SD 12.4) of their waking hours sedentary. Of the demographic and stroke-related factors, slower walking speeds were significantly and independently associated with a higher percentage of waking hours spent sedentary (p = 0.001) and uninterrupted sedentary bouts of >30 and >60 min (p = 0.001 and p = 0.004, respectively). Regression models explained 11–19% of the variance in total sedentary time and time in prolonged sedentary bouts.

**Conclusion:** We found that variability in sedentary time of people with stroke was largely unaccounted for by demographic and stroke-related variables. Behavioral and environmental factors are likely to play an important role in sedentary behavior after stroke. Further work is required to develop and test effective interventions to address sedentary behavior after stroke.

**Introduction**

Stroke is the second most common cause of death and the third leading cause of disability worldwide, with the burden expected to increase during the next 20 years. Almost 40% of the people with stroke have a recurrent stroke within 10 years, making secondary prevention vital. High amounts of sedentary time have been found to increase the risk of cardiovascular disease, particularly when the sedentary time is accumulated in prolonged bouts. Sedentary behavior, as defined as "any waking behavior characterized by an energy expenditure ≤1.5 Metabolic Equivalent of Task (METS) while in a sitting, reclining or lying posture." Studies in healthy people, as well as people with diabetes and obesity, have shown that reducing the total amount of sedentary time and/or breaking up long periods of uninterrupted sedentary time, reduces metabolic risk factors.
associated with cardiovascular disease.\textsuperscript{6,9,10,12–15} Recent studies have shown that people living in the community after stroke spend more time each day sedentary, and more time in uninterrupted bouts of sedentary time compared to age-matched healthy peers.\textsuperscript{18–20} Reducing sedentary time and breaking up long sedentary bouts with short bursts of activity may be a promising intervention to reduce the risk of recurrent stroke and other cardiovascular diseases in people with stroke.

To develop effective interventions, it is important to understand the factors associated with sedentary time in people with stroke. Previous studies have found associations between self-reported physical function after stroke and total sedentary time, but inconsistent results with regards to the relationship of age, stroke severity, and walking speed with sedentary time.\textsuperscript{20,21} These results are from secondary analyses of single-site observational studies, not powered to address associations, and inconsistent in the methods used to determine waking hours; thus making direct comparisons between studies difficult.\textsuperscript{20,21} Individual participant data pooling, with consistent processing of wake time data, allows novel exploratory analyses of larger datasets with greater power.

By pooling all available individual participant data internationally, this study aimed to comprehensively explore the factors associated with sedentary time in community-dwelling people with stroke. Specifically, our research questions were: (1) What factors are associated with total sedentary time during waking hours after stroke? (2) What factors are associated with time spent in prolonged sedentary bouts during waking hours?

**Methods**

**Study design**

This was an exploratory data pooling study, in which existing individual participant data were used for secondary analyses. By searches of databases, trial registries, and word of mouth, potentially eligible datasets were identified, and authors were invited to contribute their individual participant data and raw activity monitor data. The study was approved by the Human Research Ethics Committee of The University of Newcastle (H-2016–0427).

**Study selection**

Datasets from studies were included if they met the following criteria:

1. Included adults with stroke who were living in the community,
2. Measured sedentary behavior using the activPAL monitor (PAL Technologies Ltd, Glasgow, United Kingdom),
3. The ethical approval and informed consent for the data collection permitted the use of the data for secondary analyses,
4. The available data was not influenced by any form of intervention.

Authors of original studies provided de-identified datasets. Factors included in the datasets were mapped by one author (WH) in consultation with the co-authors. A list of factors of interest was created a priori (see Box 1), based on previous research in determinants of sedentary time and consideration of other relevant stroke-related factors.\textsuperscript{20–28} For each dataset, we determined which factors were measured and what measurement instrument was used. Where different measurement instruments were used for the same factor, we sought valid methods to categorize or dichotomize data to facilitate data pooling (see supplementary Box 1 for the conversion methods). Where the original studies included repeated measures, we included data from one time-point only and used the time-point with the least missing data or at baseline in the case of intervention trials.

**Activity monitor data**

We chose to only include data on sedentary time that was measured using the activPAL monitor (PAL Technologies Ltd, Glasgow, United Kingdom) because it is highly reliable (Intraclass correlation coefficient 0.79–0.99) and valid (98–100% accuracy) for measuring sedentary time and posture transitions during daily life in people with stroke.\textsuperscript{29–31} The ActivPAL uses an inclinometer worn on the anterior side of the thigh to determine if someone is either sedentary (sitting, lying or reclining), standing or walking making it a highly valid

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**Box. 1 Factors of interest determined a priori.**

**Demographics**
- Age
- Sex
- Employment status
- Socio-economic status
- Education attainment
- Living status

**Personal factors**
- Body Mass Index
- Smoking
- Levels of moderate to vigorous physical activity
- Comorbidities

**Environmental aspects**
- Season of accelerometer data collection

**Stroke related factors**
- Type of stroke
- Time since stroke
- Stroke severity

**Impairments**
- Upper and lower extremity impairment
- Vision impairment

**Walking ability**
- Walking speed
- Walking capacity (distance)
- Use of walking aids

**Physical ability**
- Self-reported physical function
- Independence in activities of daily living

**Cognition and mood**
- Cognitive ability
- Fatigue
- Anxiety
- Depression
and accurate monitor to determine sedentary time.\textsuperscript{29–31} A conversion to METs is also possible.\textsuperscript{29–31} Event files from all participants were combined into one dataset. To identify waking hours, a custom algorithm was developed based on previously published codes.\textsuperscript{32} The algorithm aggregated sleep time based on the largest bout of sitting/lying time within a 24-h period and then aggregated adjacent bouts of sitting/lying time where these bouts were interrupted by short bursts of activity, i.e. to account for getting up to the toilet overnight (see Appendix for more details). Our previous work has found that any three days of monitoring, regardless of weekend or weekday, is sufficient to accurately represent habitual physical activity over seven days.\textsuperscript{33}

Data processing and analyses

From the activPAL data during waking hours, the percentage of total sedentary time and the percentage of waking hours spent in prolonged bouts of sedentary time was determined. Two variables were created for prolonged bouts: percentage of sedentary time in bouts \(>30\) min and percentage of sedentary time in bouts \(>60\) min.\textsuperscript{9,10,12,18} Linear regressions (adjusting for age, gender, and study) were conducted to determine the association of individual factors with percentage of total sedentary time, percentage of sedentary time in bouts \(>30\) min, and percentage of sedentary time in bouts \(>60\) min. All factors and residuals (from regression analyses) were checked for normality and where needed the appropriate transformations were computed. Factors that were found significantly associated with univariable regressions (\(p < 0.05\)) were included in the multivariable regressions. We first determined the coverage of factors across studies and then conducted the multivariable regressions with the best coverage of factors across studies and the highest sample sizes. To avoid collinearity, if correlations between independent factors were higher than \(r = 0.850\) one factor was removed from the analyses.\textsuperscript{34,35} Both forward and backward stepwise linear regressions were run. Based on the 1:10 rule by Peduzzi et al.,\textsuperscript{36} a sample of at least \(n = 250\) was needed to be able to include all the factors we identified \textit{a priori} (Box 1). All analyses were conducted with R statistical software, version 3.3.3 and IBM SPSS statistics version 22.

Results

Participant characteristics

Ten datasets were identified that met the inclusion criteria and we were able to obtain individual participant data from 9 (90%), including \(n = 350\) individual participants (Table 1). In all, \(n = 274\) (78%) individual participants contributed at least three days of valid activPAL data. There were no differences in demographics between the original (\(n = 350\)) and final (\(n = 274\)) sample (Table 2). On average, participants spent 69 (Standard Deviation 12)% of waking hours sedentary, 40 (SD 16)% of waking hours in sedentary bouts \(>30\) min and 23 (SD 15)% of waking hours in sedentary bouts \(>60\) min. Only age and gender were reported in all studies; other variables were reported in between 3 (33%) and 8 (89%) of included studies (Supplementary Table 1).

Factors associated with total sedentary time

The results of the univariable regression (adjusting for age, gender, and study) for percentage of total sedentary time are shown in Table 3. Body mass index (\(p = 0.048\)), stroke severity (\(p = 0.035\)), walking speed (\(p < 0.001\)), walking capacity (\(p < 0.001\)), walking aid use (\(p < 0.001\)), degree of independence in activities of daily living (\(p = 0.014\)), and anxiety (\(p = 0.028\)) were all significantly associated with percentage of total sedentary time. As walking speed and walking capacity were highly correlated (\(r = 0.897\)), and more data were available across the datasets for walking speed, only walking speed was included in the multivariable regression analyses. Only walking speed remained significant in the multivariable regression model (\(p = 0.001\), see Table 4), which explained 14% of the variance in percentage of total sedentary time.

Factors associated with time spent in prolonged sedentary bouts

The results of the univariable regression (adjusting for age, gender, and study) for percentage of sedentary time in bouts \(>30\) min and percentage of sedentary time in bouts \(>60\) min are shown in Table 3. Body mass index (\(p = 0.024\) and \(p =

<table>
<thead>
<tr>
<th>Author</th>
<th>Country</th>
<th>n</th>
<th>Design</th>
<th>Time since stroke</th>
<th>Walking ability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dean*</td>
<td>Australia</td>
<td>4</td>
<td>Intervention</td>
<td>&lt; 2 years</td>
<td>Able to walk</td>
</tr>
<tr>
<td>English 2016</td>
<td>Australia</td>
<td>48</td>
<td>Observational</td>
<td>&gt; 6 months</td>
<td>Able to walk independently</td>
</tr>
<tr>
<td>Ezeugwu*</td>
<td>Canada</td>
<td>30</td>
<td>Intervention</td>
<td>2–4 months</td>
<td>Able to walk ≥ 5 m independently, no aids</td>
</tr>
<tr>
<td>Jones 2016</td>
<td>Australia</td>
<td>21</td>
<td>Intervention</td>
<td>No criteria specified; recruitment from general population</td>
<td>Able to walk ≥ 50 m, no aids</td>
</tr>
<tr>
<td>Kuys*</td>
<td>Australia</td>
<td>29</td>
<td>Intervention</td>
<td>No criteria specified; recruitment from general population</td>
<td>Able to walk 10 m independently</td>
</tr>
<tr>
<td>Mahendran 2016</td>
<td>Australia</td>
<td>36</td>
<td>Observational</td>
<td>No criteria specified; recruitment from general population</td>
<td>No criteria specified</td>
</tr>
<tr>
<td>Paul*</td>
<td>United Kingdom</td>
<td>56</td>
<td>Intervention</td>
<td>Discharged from active rehabilitation</td>
<td>Able to walk independently</td>
</tr>
<tr>
<td>Simpson*</td>
<td>Australia</td>
<td>30</td>
<td>Observational</td>
<td>No criteria specified; recruitment from rehabilitation ward</td>
<td>No criteria specified</td>
</tr>
<tr>
<td>Tiegues 2015</td>
<td>United Kingdom</td>
<td>96</td>
<td>Observational</td>
<td>No criteria specified; recruitment from rehabilitation ward</td>
<td>No criteria specified</td>
</tr>
</tbody>
</table>

*Data from ongoing trials
To check whether this confounded results, we categorized the time since stroke into three epochs (1 to 3 months, 3 to 6 months and >6 months) and re-ran the regression models for the percentage of total sedentary time using this ordinal variable. This did not change the results.

### Discussion

We pooled data from 274 individuals from three countries and found that people with stroke spent on average 69% of waking hours sedentary. Slower walking speed was the only factor independently associated with more total sedentary time, and more time spent in prolonged bouts of sedentary behavior. However, our models accounted for only a small proportion of the variance in sedentary behavior, suggesting that other factors not measured in the participants included in this study are also important.

Our findings in relation to walking speed are consistent with a previous study which found both slower walking speed, and other measures of poorer physical function (in this case the Stroke Impact Scale) were associated with greater sedentary time.\(^21\) However, walking speed may also be a proxy measure for general health and co-morbidities.\(^39–41\)

In older people, walking speed is an important predictor of a number of adverse outcomes such as falls, activities of daily living difficulties, disability, institutionalization, comorbidities, and mortality.\(^39–43\) Further research is needed to determine whether there is a direct causal pathway between slow walking speed and high sedentary time, or if it is a proxy measure of general health. It is possible that interventions aimed at improving the walking abilities of people with stroke...

### Table 2. Participant demographics.

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>All available data</th>
<th>Pooled data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample size, n</td>
<td>350</td>
<td>274</td>
</tr>
<tr>
<td>Mean (SD) across studies</td>
<td>39 (25)</td>
<td>30 (15)</td>
</tr>
<tr>
<td>Sex, number male (%)</td>
<td>213 (61)</td>
<td>167 (61)</td>
</tr>
<tr>
<td>Age, (yr) mean (SD)</td>
<td>66 (14)</td>
<td>66 (13)</td>
</tr>
<tr>
<td>Time since stroke (mth) mean (SD)</td>
<td>17 (28)</td>
<td>18 (29)</td>
</tr>
</tbody>
</table>

### Table 3. Univariate regressions.

<table>
<thead>
<tr>
<th>Factor</th>
<th>Number participants, n (number studies)</th>
<th>Missing data within studies, n (%)</th>
<th>Time spent sedentary</th>
<th>Time spent in sedentary bouts &gt;30 min</th>
<th>Time spent in sedentary bouts &gt;60 min</th>
</tr>
</thead>
<tbody>
<tr>
<td>Demographics</td>
<td></td>
<td></td>
<td>p value</td>
<td>Adjusted R²</td>
<td>p value</td>
</tr>
<tr>
<td>Educational level</td>
<td>52 (3)</td>
<td>0 (0%)</td>
<td>0.564</td>
<td>−0.052</td>
<td>0.709</td>
</tr>
<tr>
<td>Living arrangements</td>
<td>144 (6)</td>
<td>0 (0%)</td>
<td>0.107</td>
<td>0.005</td>
<td>0.524</td>
</tr>
<tr>
<td>Personal factors</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BMI</td>
<td>205 (7)</td>
<td>27 (13%)</td>
<td>0.048</td>
<td>0.023</td>
<td>0.024</td>
</tr>
<tr>
<td>Smoker</td>
<td>171 (4)</td>
<td>6 (4%)</td>
<td>0.317</td>
<td>0.006</td>
<td>0.971</td>
</tr>
<tr>
<td>Comorbidities</td>
<td>147 (4)</td>
<td>0 (0%)</td>
<td>0.359</td>
<td>0.005</td>
<td>0.295</td>
</tr>
<tr>
<td>Stroke related factors</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Type of stroke</td>
<td>198 (6)</td>
<td>6 (3%)</td>
<td>−0.067</td>
<td>0.024</td>
<td>0.214</td>
</tr>
<tr>
<td>Time since stroke</td>
<td>268 (8)</td>
<td>3 (1%)</td>
<td>0.893</td>
<td>0.010</td>
<td>0.468</td>
</tr>
<tr>
<td>Stroke severity</td>
<td>118 (3)</td>
<td>2 (2%)</td>
<td>0.035</td>
<td>0.030</td>
<td>0.019</td>
</tr>
<tr>
<td>Walking ability</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Walking speed</td>
<td>195 (6)</td>
<td>6 (3%)</td>
<td>−0.001</td>
<td>0.156</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Walking capacity (distance)</td>
<td>149 (5)</td>
<td>46 (31%)</td>
<td>−0.001</td>
<td>0.064</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Walking aid</td>
<td>216 (7)</td>
<td>4 (2%)</td>
<td>−0.001</td>
<td>0.064</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Physical ability</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Degree of ADL independence</td>
<td>197 (6)</td>
<td>4 (2%)</td>
<td>0.014</td>
<td>0.045</td>
<td>0.003</td>
</tr>
<tr>
<td>Cognition and mood</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cognitive function</td>
<td>145 (5)</td>
<td>37 (26%)</td>
<td>0.864</td>
<td>0.004</td>
<td>0.445</td>
</tr>
<tr>
<td>Fatigue</td>
<td>192 (6)</td>
<td>36 (19%)</td>
<td>0.084</td>
<td>0.027</td>
<td>0.101</td>
</tr>
<tr>
<td>Mood disorder</td>
<td>194 (6)</td>
<td>8 (4%)</td>
<td>0.235</td>
<td>0.019</td>
<td>0.179</td>
</tr>
<tr>
<td>Anxiety</td>
<td>153 (4)</td>
<td>3 (2%)</td>
<td>0.028</td>
<td>0.031</td>
<td>0.079</td>
</tr>
<tr>
<td>Depression</td>
<td>175 (5)</td>
<td>8 (5%)</td>
<td>0.055</td>
<td>0.027</td>
<td>0.118</td>
</tr>
</tbody>
</table>

All regressions corrected for age, gender, and study. Bolded values indicate statistical significance.

BMI = body mass index, ADL = activities of daily living
might help reduce the total sedentary time and the time spent sedentary in prolonged bouts. However, this premise requires testing in clinical trials.

We found few other factors were independently associated with high sedentary behavior. This is in contrast to previous studies. In older adults without stroke, age, gender, education level, living arrangements, body mass index, smoking status, and independence in activities of daily living, were all found to be associated with sedentary behavior.22,25–27 In previous studies of people with stroke both age and stroke severity were associated with sedentary behavior.20,21 In people with multiple sclerosis, both disease severity and physical ability are reported to be associated with high sedentary time.44 Taken together, this suggests that the factors associated with high sedentary time may differ between population groups. This is important to consider when developing interventions to reduce sedentary behavior.

In our analyses, the regression models accounted for only a small proportion of the variance in sedentary behavior. It is likely that environmental and behavioral factors may also influence sedentary time in people with stroke, and this should be taken into consideration when designing interventions to reduce sedentary behavior in this population. Such interventions will need to be carefully developed and include strategies to address both the factors influencing sedentary behavior, and the barriers and motivations to increase light, moderate, and vigorous physical activity. Systematic reviews of clinical trials in other populations (healthy and older adults, those with diabetes or obesity) have highlighted the importance of developing interventions specifically targeted to reduce sedentary time, as such programs are more effective for reducing sedentary time compared with interventions that aim to increase physical activity alone.45,46 An international consensus framework for sedentary behavior research across all population groups,23 as well as qualitative research involving people with stroke,47 highlights the importance of the environment, psychology (including motivation), education, and behavior as determinants of sedentary time. Development of effective interventions to address high levels of sedentary time in people with stroke will need to take all these factors into consideration.

### Strengths and limitations

We pooled all available individual participant activity monitor data, and completed a novel exploratory analysis on a large dataset, with sufficient statistical power. We choose this novel data pooling methodology (instead of for instance meta-analyses) to be able to conduct independent secondary analyses using raw data. This also allowed the inclusion of data from ongoing and unpublished studies. We did not complete systematic literature searches, meaning that it is possible that some potentially relevant datasets were missed. The extensive international collaboration that was the foundation of this study allows confidence that we captured the vast majority of trials that have included activPAL data. The large dataset provides confidence in the results. We re-processed all raw activity monitor files using a custom-built algorithm to consistently and systematically identify sleep-wake time without manual error.48 We decided to use only data in which the activPAL was used to measure sedentary time. This decision was based on the fact that different activity monitors use different methods to determine the sedentary time and movement, and therefore combining raw data from different monitors would introduce bias.49,50 Two studies have shown the incompatibility of data from different monitors.49,50 Only including activPAL data provides confidence in the validity of data between datasets. We acknowledge that this reduced the number of datasets we were able to include. Since the activPAL is highly reliable in the determination of sedentary behavior it is a commonly used monitor and therefore enabled the inclusion of most of the data that is available.

### Table 4. Multivariable regression.

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Number participants, n (number studies)</th>
<th>Missing data within studies, n (%)</th>
<th>p value</th>
<th>Unstandardized β (95% CI)*</th>
<th>Standardized β*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time spent sedentary</td>
<td>BMI 182 (7) 69 (27%)</td>
<td>0.071 (10.26)</td>
<td></td>
<td>-0.190 (0.108 to 0.272)</td>
<td>-0.390</td>
</tr>
<tr>
<td></td>
<td>Stroke severity 118 (7) 133 (53%)</td>
<td>0.231 (0.139)</td>
<td></td>
<td>0.001 (0.115)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Walking speed 195 (7) 56 (22%)</td>
<td>0.048 (0.007)</td>
<td></td>
<td>-0.115 (0.048 to 0.206)</td>
<td>-0.390</td>
</tr>
<tr>
<td></td>
<td>Walking aid 197 (7) 54 (22%)</td>
<td>0.048 (0.007)</td>
<td></td>
<td>0.001 (0.115)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Degree of ADL independence 197 (7) 54 (21%)</td>
<td>0.532 (0.78)</td>
<td></td>
<td>0.001 (0.115)</td>
<td></td>
</tr>
<tr>
<td>Time spent in sedentary bouts &gt;30 min</td>
<td>Anxiety 153 (7) 98 (39%)</td>
<td>0.512 (0.77)</td>
<td></td>
<td>-0.153 (0.253 to 0.070)</td>
<td>-0.401</td>
</tr>
<tr>
<td></td>
<td>BMI 182 (7) 69 (27%)</td>
<td>0.049 (0.007)</td>
<td></td>
<td>0.001 (0.115)</td>
<td>0.222</td>
</tr>
<tr>
<td></td>
<td>Stroke severity 118 (7) 133 (53%)</td>
<td>0.182 (0.151)</td>
<td></td>
<td>0.001 (0.115)</td>
<td>0.222</td>
</tr>
<tr>
<td></td>
<td>Walking speed 195 (7) 56 (22%)</td>
<td>-0.001 (0.235 to 0.070)</td>
<td></td>
<td>0.001 (0.115)</td>
<td>0.222</td>
</tr>
<tr>
<td></td>
<td>Walking aid 197 (7) 54 (22%)</td>
<td>0.413 (0.100)</td>
<td></td>
<td>0.001 (0.115)</td>
<td>0.222</td>
</tr>
<tr>
<td></td>
<td>Degree of ADL independence 197 (7) 54 (21%)</td>
<td>0.351 (0.113)</td>
<td></td>
<td>0.001 (0.115)</td>
<td>0.222</td>
</tr>
<tr>
<td>Time spent in sedentary bouts &gt;60 min</td>
<td>BMI 182 (7) 69 (27%)</td>
<td>0.110 (0.186)</td>
<td></td>
<td>0.013 (0.115)</td>
<td>0.222</td>
</tr>
<tr>
<td></td>
<td>Stroke severity 118 (7) 133 (53%)</td>
<td>0.132 (0.177)</td>
<td></td>
<td>0.013 (0.115)</td>
<td>0.222</td>
</tr>
<tr>
<td></td>
<td>Walking speed 195 (7) 56 (22%)</td>
<td>0.004 (0.131)</td>
<td></td>
<td>0.001 (0.115)</td>
<td>0.222</td>
</tr>
<tr>
<td></td>
<td>Walking aid 197 (7) 54 (22%)</td>
<td>0.670 (0.054)</td>
<td></td>
<td>0.001 (0.115)</td>
<td>0.222</td>
</tr>
<tr>
<td></td>
<td>Degree of ADL independence 197 (7) 54 (21%)</td>
<td>0.333 (0.122)</td>
<td></td>
<td>0.001 (0.115)</td>
<td>0.222</td>
</tr>
<tr>
<td></td>
<td>Fatigue 192 (7) 59 (24%)</td>
<td>0.441 (0.091)</td>
<td></td>
<td>0.001 (0.115)</td>
<td>0.222</td>
</tr>
</tbody>
</table>

All regression were corrected for age, gender, and study. All regression analyses included data from: English, Ezeugwu, Kuys, Mahendran, Paul, Simpson, and Tieges. Bolded values indicate statistical significance.

*Since forward and backward methods were used for the regressions, not all data is available for the non-significant variables.
While we pooled all the available individual participant data, not all factors of interest we identified a priori were available. Furthermore, even where the same construct (for example, depression, anxiety, physical ability) was measured, the variability in the outcome measures used necessitated categorizing or dichotomizing data. To facilitate comparability of research findings and future data pooling studies, greater consistency in outcome measurement tools used is required. The international Stroke Recovery and Rehabilitation Round Table group recently conducted a consensus project and have published recommendations for a core dataset for all stroke recovery and rehabilitation trials.

Though the cut-offs of 30 and 60 min, used as an outcome variable for prolonged sedentary time, in their origin are arbitrary they have been used in previous studies on the risk of sedentary behavior. These studies have shown that the risk of cardiovascular disease increases even more when the sedentary time is accumulated in these prolonged bouts. Therefore these cut-offs provide a standard metric for prolonged sedentary time. This study included only people with stroke living in the community, and for the most part only those able to walk independently, therefore results have limited generalizability beyond this group.

Conclusion

We found that variability in sedentary time of people with stroke was largely unaccounted for by demographic and stroke-related variables. Behavioral and environmental factors are likely to play an important role in sedentary behavior after stroke. Further work is required to develop and test effective interventions to address sedentary behavior after stroke.

Disclosure of interest

Authors have no conflicts of interest to declare.

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Appendix Sleep/Non-wear time identification algorithm

Objective
Identify the single longest daily period of sleep/non-wear activity in order to delineate what is considered as wake period.

Methods
The simple prescription given by Elisabeth Winkler et al. (Winkler et al. (2016)) was used as a starting point.

Recorded data consists of activPAL timestamped events, typified as sitting/lying, standing and walking. Events represent the longest continuous uninterrupted activity of each class. There is one event per step.

It was observed during initial implementation of Winkler’s prescription that sleep period patterns for this cohort exhibit a more interrupted pattern, requiring a more flexible approach to correctly identify periods. The algorithm was modified as shown below.

Pseudocode:

Definitions
- **SL**: sleep period. A sleep period consists of a “chain” of “nearby” events, primarily of class lying, that accounts for the longest aggregated resting period in a 24hr interval. The meaning of “chain” and “nearby” is made precise through the pseudocode. A sleep period is defined by its start and end times, which must be start and end times of lying-class events, and all events encompassed in between. duration(SL) is the total accumulated time in lying events in SL.
- **e1, e2**: represent generic lying events. A lying event carries an aggregation opportunity window of length of 12 min + 10% of event duration, capped at 45 min. Longer events have longer opportunity windows to be aggregated into the sleep event chain. The opportunity window of a lying event is denoted below as opp.window(e).
- **Ev**: is the list of all events in a 24hr interval for an individual, from noon to noon next day.
- **LEv**: is the list of lying events longer than 30 min in Ev, to be considered for aggregation in the sleep period (“long lying events”)
- **Tlev**: is the total time accumulated in long lying events in the day. Used in considering an alternative chain of lying events for the sleep period.

Algorithm

**Note: how to read pseudocode.** A simplified pseudocode of the algorithm is shown below, while and for each imply a loop, if imply testing a condition; the level of indentation indicates the actions included in the repeating part of the loop or the true outcome of the test. For clarity, abnormal termination conditions are excluded from the algorithm below.

```
Input: Ev
Output: SL

LEv = get lying events longer than 30 minutes from Ev
Tlev = sum of event duration for events in LEv
el = find longest unused event from LEv
A:
    initialise sleep chain SL with el
    mark el as used
    while there are unused events in LEv and SL modified since last pass
        for each unused event e2 in LEv, in descending duration order
            if opp.window(e2) overlaps SL
                add e2 to SL
                mark e2 as used
            endif
        endfor
    endwhile
    if duration(SL) < 0.4 Tlev and there are unused events in LEv
        el = find longest unused event from LEv
        mark all events in LEv as unused
        mark el as used
        restart from A:
    endif
```

Running environment
```
## [1] backports_1.0.5 magrittr_1.5 rprojroot_1.2 tools_3.3.3
## [2] digest_0.6.12 stringi_1.1.5
## [3] htmltools_0.3.5 yaml_2.1.14 Rcpp_0.12.10
## [4] stringr_1.2.0 knitr_1.15.1 rmarkdown_0.10
## [5] tools_3.3.3
## [6] htmlwidgets_1.2.0 digest_0.6.12
## [7] knitr_1.15.1
## [8] evaluate_0.10
```

References

