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Exploring centricity of activity spaces: From measurement to the identification of personal and environmental factors

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ABSTRACT

It has been known for long that people tend to form clusters of activity places, typically around their daily life centers, for a number of reasons such as to facilitate their daily mobility. Despite this knowledge, there is little research done on identifying and measuring this type of travel behavior. The exiting measures of activity space dispersion often exclusively rely on overall numeric assessment and overlook the geographical distribution of activity places. In this study, we introduce centricity as a new dimension of activity spaces and we operationalize it as a clusterization of activity places. Delineation of clusters in this approach adds a spatial component to the measure. This enables the scrutiny of activity clusters and possible personal and environmental factors contributing to their formation. Furthermore, using data collected through an online mapping survey, we study the centricity of individual activity spaces and classify them into three groups of monocentric, bicentric, and polycentric. Our study of citizens of Helsinki metropolitan area aged 55–75 shows that monocentric activity spaces are the most common type among the study group. Nevertheless, a considerable share of extra-neighborhood travels are made to denser areas of more urban characteristics. The results do not indicate any significant associations between socio-economic characteristics and centricity. However, urban form and travel mode were found to be significantly associated with centricity. Overall, the findings show that use of centricity can help broaden our understanding of individual travel behavior and in turn contribute to interventions promoting healthy and sustainable travel behavior.

1. Introduction

Studying travel behavior has been at the center of scholarly interest for decades, with its wide applications extending to fields such as, transportation engineering (Young and Lachapelle, 2017), gender studies (Nobis, 2005; Baratian-Ghorghi and Zhou, 2015), transportation emissions (Rahman and Idris, 2017), urban planning (Helbic, 2017), and health studies (Perchoux et al., 2013). A growing number of studies suggest that for a comprehensive understanding of individual travel behavior, researchers need to focus not only on trips, but also on the space containing them. Consequently, activity spaces, traditionally defined as a set of geographically distributed locations which are physically contacted by individuals (Reynolds and Horton, 1971), have drawn scholarly attention. Despite the extensive amount of literature on the topic of activity spaces, some researchers believe that a full understanding of these complicated structures is yet to be achieved (Hasanzadeh et al., 2017; Li and Tong, 2016). Activity spaces are multidimensional constructs and not all their dimensions have been sufficiently investigated. We believe that centricity of activity spaces – identification of centers of activity – is one of these dimensions that need further investigation to provide better understanding of these spaces.

As elaborately reviewed in a number of studies (e.g. Golledge, 1997; Patterson and Farber, 2015; Hasanzadeh et al., 2017), researchers coming from different fields have taken different approaches to model and understand activity spaces. A considerable amount of this body of research has thus far focused on methods of delineating these spaces. Accordingly, researchers have proposed a wide range of methods and models for representing individual activity spaces (e.g. Sherman et al., 2005; Fan and Khattak, 2008; Hasanzadeh et al., 2017, 2018; Laatikainen et al., 2018). However, thus far little effort has been put on exploring different dimensions of activity spaces and providing measures of understanding them. In a virtually isolated effort, Perchoux et al. (2014) in an attempt to identify populations with specific mobility needs, explore different dimensions of activity spaces to study spatial behavior of individuals and explore its associations with socio-demographic characteristics and choice of transportation modes. Continuing the same line of thought, Hasanzadeh and colleagues (Hasanzadeh et al., 2018) use a wider range of activity space measures, and explore different types of activity and travel related information they can each
capture. Among the measures discussed in these studies, a considerable share of them are related to the assessing the spatial patterns and distribution of individual activity places. Measures such as area and perimeter of activity space capture the overall spatial extent of travel (Sherman et al., 2005), whereas measures such as average distance to destinations (Perchoux et al., 2014), Gravelius compactness coefficient (Bendjoudi and Hubert, 2002), elongation (Hasanzadeh et al., 2018), or Index of eccentricity (Lord et al., 2009) can indicate the overall dispersion and distribution of activity places. Further, there are other measures such as percentage of activity places within neighborhood (Hasanzadeh et al., 2018), or degree of attachment to neighborhood (Perchoux et al., 2014), which can show the extent of concentration of activity places around an individual’s residential environment.

Although such measures provide useful information on travel and activity patterns of individuals, they have certain limitations. For instance, measures of dispersion related to the geometric characteristics of activity spaces ignore the internal heterogeneity of its component activity places and the complexity of daily mobility (Matthews, 2011; Kwan, 2013; Wei et al., 2018). Human activities are often multi-centered and each center serves an aspect of daily life for the individual (Wei et al., 2018). Although this heterogeneity of activity spaces has been acknowledged in previous research (Axhausen et al., 2002), and has been occasionally addressed in modeling activity spaces (Wei et al., 2018; Hasanzadeh et al., 2018), it has rarely been explored as a dimension of activity space; a dimension which can provide new insights into individual activity spaces and help us identify the spatial and individual determinants of dispersed travel behavior. Furthermore, the existing indicators provide us with a measurable unit of dispersion of activity spaces while missing the spatial component. This makes it challenging to investigate different travel behaviors in relation to their respective geographical context. Therefore, a clusterization approach aiming to measure and map the activity clusters of individuals can provide us with new insights to the environmental determinants of different travel patterns.

Despite the need, to the best of the authors’ knowledge, this has not empirically been investigated in literature. Perhaps the closest attempt for addressing this can be found in Flamm and Kaufmann’s conceptualization of ‘personal network of usual places (NUP)’ (2006). While investigating activity spaces, they define NUP as a network encompassing a number of fixed geographical points and their interconnecting routes that an individual visits on a recurring basis (Flamm and Kaufmann, 2006). Using qualitative interviews, Flamm and Kaufmann (2006) report that individuals often create clusters of activity points which are typically around individual’s life centers, i.e. places such as home or workplace that are important in the conduct of everyday life. These clusters are not typically too large so that the individual can travel between activity points on foot or bike (Flamm and Kaufmann, 2006). Furthermore, previous research shows that people often do their most frequent activities near their place of residence (Flamm and Kaufmann, 2006; Neutens et al., 2012). In other words, the activity cluster encompassing individual’s home, typically includes the most frequent activities while activity points located further from home are generally less frequently visited by an individual.

One question that usually arises when the dispersion of travel behavior and activity places are discussed, is in fact the existence of extra-neighborhood visits. A clustered approach can facilitate the identification of such travel behaviors and help us investigate their possible environmental determinants. One of the most common explanations for this question is the one provided by the compensation hypothesis (Hall and Page, 2014; Strandell and Hall, 2015). The compensation hypothesis assumes that the lack of leisure opportunities, such as green areas and waterfronts, in people’s residential environments, creates more travel to exurban green spaces or other long-distance leisure areas (Hall and Page, 2014). However, not all studies support this hypothesis. An empirical study in the Dutch city of Arnhem (Maat and de Vries, 2006), as well as a similar study conducted in Barcelona (Muñiz et al., 2013), reject the hypothesis and show that the lack of green space in one’s vicinity does not generally result in compensation behavior. Maat and de Vries (2006) explain that this may be a result of self-selection in the residential choice process. Furthermore, one can argue that the compensation hypothesis can go beyond its most common definition and include compensation for other urban characteristics such as density and a variety of services and amenities.

With the extensive literature in the field, there is little doubt about the importance of understanding individual travel behavior. Particularly, the measures of activity space related to the dispersion of activities are of utmost scholarly importance. Large activity spaces made of dispersed activity centers typically involve longer commutes. This type of travel behavior can potentially discourage use of active travel modes and lead to further concerns related to the sedentary behavior of individuals and its empirically-demonstrated health complications (Northridge and Freeman, 2011; Zapata-Diemedi et al., 2017). Furthermore, extensive motorized travel is considered as an environmentally detrimental behavior that should be ideally minimized (Millard-Ball and Schipper, 2011).

The present study aims to take a step toward filling the existing conceptual and methodological gaps in understanding dispersion of travel behavior using activity spaces by introducing centrivity. We conceptually define centrivity as an acknowledgment of the fact that activity spaces of individuals are not always concentrated around their homes, but can form clusters throughout the space. Although comparable to the multi-centered characteristic of activity spaces discussed in previous research (Wei et al., 2018), this study takes a novel methodological step by introducing centrivity as a measure of activity point clusterization and subsequently providing a classification of activity spaces based on it. In this approach, not only the degree of one’s activity space is measured, but also the activity clusters can be identified and delineated. This can facilitate the analysis of travel patterns in relation to the environmental characteristics. At the same time, using a dataset collected through an online mapping survey, we conduct an empirical case study of aging adults (SS–75) in Helsinki metropolitan area. In this empirical part, we pursue a twofold goal. First, to implement centrivity as a practical tool for measuring dispersion of activity spaces. Second, to investigate the relationship between centrivity, urban form, background variables, and use of different travel modes in the study area.

In the following sections, we will present the used methodology and discuss the results. Consequently, we will conclude the paper by underlining the significance of our findings, identifying existing limitations, and envisioning areas of future research.

2. Materials and methods

2.1. Data

The data was collected using softGIS methodology, a public participation GIS (PPGIS) method that combines Internet maps with traditional questionnaires (Brown and Kyttä, 2014). A random sample of 5000 residents of Helsinki metropolitan area, in Finland, aged between 55 and 75 was obtained from Finnish Population Register Center and an invitation to participate in an internet based PPGIS survey was sent to participants’ home addresses in October 2015. In the survey, respondents used an online interface to mark their daily activity points on a map. The daily activity points were defined as places individuals visit during a typical week and the categories included: leisure and recreational activity places, shopping, services, and sport facilities. For each category, examples were provided in the survey to help respondents. In addition, the respondents indicated by which transportation mode and how frequently they accessed these places. The respondents were also asked to mark on a map their home and places of their everyday environment where they feel happy and answer a series of questions about their personal life goals, background, and health. There were 1139 responses in total, 788 of which were kept for further analysis after
removing incomplete submissions. The data showed general consistency with the Statistics Finland on most socio-demographic variables (Appendix A). Fig. 1 illustrates the distribution participants’ home locations in Helsinki metropolitan area.

To study the relationships between urban structure and centricity of activity spaces, we used three measures. First, we used the Urban Zone classification provided by Finnish Environment Institute (YKR). This dataset includes a GIS-based (250 × 250 m grid of cells) classification that divides urban regions into zones according to their location in the urban form (e.g. in relation to the center), and travel-relevant variables, population characteristics, public transportation supply, building stock, and jobs (Söderström et al., 2015). For this article, we used an aggregation into three zones starting from the most central areas identified as pedestrian zone, through to outer rings classified as respectively transit and car zone. Second, we used population density. The population data was provided by Statistics Finland presented as number of
residents in 1 km² grid cells. For each location, the population density was identified as the number of people living in the grid cell containing the point. Third, we measured green area coverage and proximity to water areas. The data was extracted from a larger dataset named SLICE provided by Finnish ministry of environment, which includes the land types for the whole country. In this study, areas classified as forests, parks, and green areas with recreational and sport facilities, were regarded as green areas. The green area coverage for each spatial unit (polygon) was calculated as the percentage of land classified as green. Water areas in this study include lakes and the sea.

It should be noted that the environmental characteristics of the region of study were considered in choice of these urban structural variables. Helsinki Metropolitan area is a vast region characterized by large amounts of forests and areas with access to various bodies of water. The density of the region also varies markedly from sparsely populated areas of more rural characteristics to significantly denser urban areas.

2.2. Measuring the centricity of activity spaces

We operationally define centricity as an ordinal variable of activity space measuring the multiplicity of activity centers in an individual’s activity space. Accordingly, centricity was measured and activity spaces were classified into three groups based on their level of centricity (Fig. 2). **Monocentric**: activity spaces which consist of a single cluster of activity places located in home surrounding. **Bicentric**: activity spaces which in addition to the cluster of activities around the home, have another center of activities somewhere further. **Polycentric**: activity spaces which in addition to the cluster of activities around the home, have at least two more centers of activities further from the place of residence.

As it can be seen in Fig. 3, for measuring centricity a multistep algorithm based on K-Means clustering method is used. The optimum number of clusters, in the steps where it is required, is determined using NbClust R package. NbClust uses 30 indices to determine the optimum number of clusters from the different results obtained by various combinations of number of clusters, clustering methods, and distance measures (Chaerad et al., 2014). For operational reasons and to apply the two different $r_1$ and $r_2$ parameters for the residential and extra-neighborhood cluster identification, the clustering analysis in this algorithm is run twice for each individual. In the first run, the cluster including the home point of an individual is identified. The only constraint in determining the home surrounding activity cluster is that no point in this cluster should exceed the home range distance from the centroid ($r_1$). This is to ensure that first cluster including the place of residence remains local and does not include very distant locations. The home range distance was identified using the optimization method previously used in several research (Hasanzadeh et al., 2017; Laatikainen et al., 2018). Accordingly, a Python implementation of Jenk’s method (Hasanzadeh, 2018) was applied to activity points of individuals and subsequently a goodness of variance fit statistic was utilized in order to optimize the clustering results (Jenks, 1967). The algorithm yielded a value of 3348 m as the threshold which was rounded down to 3300 m and was used as the average home range distance. It should be noted that $r_1$ is only a controlling distance to ensure the locality of the residential activity cluster and it does not mean that every point within this distance must necessarily belong to this cluster.

In the second run, the clustering analysis is performed on the remaining activity points. As Flamm and Kaufmann (2006) suggest, individuals often create clusters of activity places in order to easily travel between them by walking or possibly using a bike. Therefore, a distance constraint of $r_2 = 1000$ from cluster centroid was added to the analysis to ensure that the identified clusters remain within a reasonable and

![Fig. 3. The working flow of measuring activity space centricity. CS: cluster significance, NOP: number of points, Freq: frequency, n: number of clusters.](image-url)
actively travelable size. In order to evaluate how the choice of this distance as \( r_2 \) can affect the analysis outcomes, a sensitivity analysis was also performed. Accordingly, we compared the use of 500, 800, 1000, and 1200 m distances as \( r_2 \) and measured how big of a difference they cause in the analysis results. As illustrated in Table 1, use of the four different distances does not result in any significant changes in the frequency of different centricity levels found in the dataset.

Finally, in order to count the number of clusters, their significance was first evaluated. This was operationalized as the total frequency of visits to all locations in the cluster. Subsequently, each cluster with a total frequency of at least once a week was included in the centricity measurement.

2.3. Statistical analysis

The statistical findings of this study are presented in three forms of proportions, correlations, and varying means between groups. The statistical significance of proportions were tested using a two-by-one contingency table. Therefore, using Chi-square we tested the hypothesis that the two percentages are equal–50%. Possible existence of associations between centricity, as dependent variable, and background variables, was explored using an ordinal logistic regression. Finally, in order to test the statistical significance of differences between means of different groups one-way ANOVA was conducted.

The choice of travel modes was evaluated by identifying the dominance of active or motorized travel modes of individuals. Accordingly, individuals who had reported use of active travel modes, namely walking and cycling, in more than half of their trips were classified as dominantly active travelers. On the other hand, individuals who had reported use of motorized travel modes, namely public transportation and car, in more than half of their trips were classified as dominantly non-active travelers.

3. Results

3.1. Centricity of activity spaces

Centricity analysis was performed on individuals who had provided enough spatial data for inclusion in the analysis. This excluded individuals who had not reported any activity places in the survey. As a result of measuring centricities, activity spaces from 788 individuals were classified into three groups. Monocentric activity space was the most common type with more than 61% of participants identified as having an activity space of such characteristic. Bicentric and Polycentric activity spaces were almost equally common with respectively 20% and 19% shares of participants included in the analysis. Table 2 shows some of the descriptive characteristics of the identified clusters.

As expected, the area of activity space varies significantly between different centricity types. Accordingly, polycentric activity spaces had the biggest area, with a median of 3064 km², followed by bicentric and monocentric activity spaces, each with a median area of 415 and 36 km² respectively. It should be noted that the area of activity space was calculated as the surface of the minimum convex polygon containing all home and activity points of an individual (Perchoux et al., 2014).

We also examined how centricity correlates with other commonly used measures of activity place dispersion. Perimeter and Area of activity space indicate the overall size of the minimum convex polygon containing all home and activity points of an individual. Further, Gravelius and elongation (illustrated in Appendix B), are shape indexes occasionally used to capture the overall dispersion of activity places. As reported in Table 3, centricity is significantly positively correlated with area of activity space, perimeter, as well as the average distance from home to activity locations. However, centricity is not statistically significantly correlated with elongation and it is found to be negatively correlated with Gravelius index.

3.2. Centricity, background variables, and location in the region

A cumulative odds ordinal logistic regression with proportional odds was used to determine the associations between centricity, socio economic variables, and location of domicile in the region. As presented in Table 4, results indicate that none of the socio-economic variables are statistically significantly associated with centricity of activity spaces. On the other hand, centricity is statistically significantly associated with location of residence in the region. Moving from urban areas to areas with more suburban settings was associated with an increase in odds of higher centricity of activity spaces. In other words, in

Table 2
Descriptive characteristics of the identified activity clusters. Distances are in km. SD: standard deviation.

<table>
<thead>
<tr>
<th>Average number of markings (SD)</th>
<th>Average number of clusters (SD)</th>
<th>Average number of activity points per cluster (SD)</th>
<th>Average distance from cluster centroids to Home (SD)</th>
<th>Average distance between cluster centroids (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.86 (4.10)</td>
<td>2.1 (0.82)</td>
<td>2.9 (2.7)</td>
<td>4.8 (6.3)</td>
<td>3.6 (2.71)</td>
</tr>
</tbody>
</table>

Table 3
Correlations between different measures of activity space dispersion. (AS: activity space).

<table>
<thead>
<tr>
<th></th>
<th>Perimeter of AS</th>
<th>Area of AS</th>
<th>Average distance to activity places</th>
<th>Elongation</th>
<th>Gravelius</th>
<th>Centricity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perimeter of AS</td>
<td>1</td>
<td>0.627**</td>
<td>0.415**</td>
<td>0.105**</td>
<td>0.201**</td>
<td>0.282**</td>
</tr>
<tr>
<td>Area of AS</td>
<td>0.627**</td>
<td>1</td>
<td>0.263**</td>
<td>-0.013</td>
<td>-0.012</td>
<td>0.136**</td>
</tr>
<tr>
<td>Average distance to activity places</td>
<td>0.415**</td>
<td>0.263**</td>
<td>1</td>
<td>0.031</td>
<td>0.025</td>
<td>0.233**</td>
</tr>
<tr>
<td>Elongation</td>
<td>0.105</td>
<td>-0.013</td>
<td>0.031</td>
<td>1</td>
<td>0.901**</td>
<td>-0.054</td>
</tr>
<tr>
<td>Gravelius</td>
<td>0.201</td>
<td>-0.012</td>
<td>0.025</td>
<td>0.901**</td>
<td>1</td>
<td>-0.084</td>
</tr>
<tr>
<td>Centricity</td>
<td>0.282**</td>
<td>0.136**</td>
<td>0.233**</td>
<td>-0.054</td>
<td>-0.084</td>
<td>1</td>
</tr>
</tbody>
</table>

* Correlation is significant at the 0.05 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).

Table 4
Ordinal logistic regression results. Associations between centricity, socio-economic variables, and location in region.

<table>
<thead>
<tr>
<th></th>
<th>B</th>
<th>SE B</th>
<th>( \chi^2 )</th>
<th>p</th>
<th>95% CI Lower Bound</th>
<th>95% CI Upper Bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>Income</td>
<td>0.044</td>
<td>0.025</td>
<td>3.995</td>
<td>0.079</td>
<td>-0.005</td>
<td>0.093</td>
</tr>
<tr>
<td>Education</td>
<td>0.105</td>
<td>0.079</td>
<td>1.752</td>
<td>0.186</td>
<td>-0.051</td>
<td>0.261</td>
</tr>
<tr>
<td>Age</td>
<td>0.011</td>
<td>0.022</td>
<td>0.256</td>
<td>0.613</td>
<td>-0.032</td>
<td>0.054</td>
</tr>
<tr>
<td>Marital status = Single (vs. with partner)</td>
<td>0.092</td>
<td>0.287</td>
<td>0.103</td>
<td>0.749</td>
<td>-0.471</td>
<td>0.655</td>
</tr>
<tr>
<td>Retired = No (vs. yes)</td>
<td>-0.051</td>
<td>0.248</td>
<td>0.043</td>
<td>0.836</td>
<td>-0.538</td>
<td>0.435</td>
</tr>
<tr>
<td>Gender = male (vs. female)</td>
<td>-0.103</td>
<td>0.160</td>
<td>0.412</td>
<td>0.521</td>
<td>-0.416</td>
<td>0.211</td>
</tr>
<tr>
<td>Location in region (more suburban)</td>
<td>0.920</td>
<td>0.172</td>
<td>28.504</td>
<td>0.000</td>
<td>0.583</td>
<td>1.258</td>
</tr>
</tbody>
</table>
central urban areas people tend to have more monocentric activity spaces, whereas in suburban and rural areas polycentricity tends to be more common.

There is also a significant difference in the dominant mode of transportation between the activity space types. Participants identified with monocentric activity spaces have reported the highest use of active transportation modes compared to the other two groups (62% of total trips). Participants with bicentric and polycentric activity spaces have reported 42% and 29% use of active transportation modes respectively.

An analysis of variance (ANOVA) on these scores yielded significant variation among groups, F(2, 773) = 5.24, p < .001. A post hoc Tukey test showed that the difference in use of active travel modes differed significantly between all pairs of activity space types at p < .001.

### 3.3. Traveling outside neighborhood, why and where to?

A negative correlation between distance of activity points from participants’ homes and their frequency of visit implies that people tend to do their most frequent activities in closer distances to their homes (r (4998) = −0.11, p < .001). Similarly, the average frequency of visits to activity points within home range distance (8.17 times/month) is statistically significantly bigger than activity points outside this distance (5.24 times/month, P < .001). But what motivates these occasional extra-neighborhood travels?

To answer this question we compared the values of three urban structural variables (namely greenness, population density, and proximity to water) within home range of individuals, with those in activity clusters located outside the home ranges (Table 5). The majority of participants with bicentric and polycentric activity spaces travel to distant areas that are more densely populated than their own area of residence (62%). In the same line, only 28% of participants identified with these two activity space types, travel to areas which are greener than their home cluster. Female participants form a bigger proportion of these ‘density-seeking’ travelers (61%), compared to their share among all study participants (56%). This density-seeking travel behavior also manifests in higher tendency of people living in suburban areas to travel to areas outside their home range with more urban settings. This can be seen as a positive correlation between the population density difference at two ends of travels and urban zone number at residential areas of density-seeking travelers (r(409) = 0.44 p = .000, 1 to 3: most urban to most suburban). Furthermore, a relatively small ratio of people regularly traveling outside their home ranges, have reported visiting areas near water (27%). The majority of these individuals are residents of central areas (77%).

### 4. Discussion

Many researchers agree that activity spaces are complicated constructs and understanding them requires comprehensive investigation. Activity spaces are multidimensional, with each dimension elucidating certain aspects of mobility behavior of individuals (Perchoux et al., 2014; Hasanzadeh et al., 2018). Motivated by few scattered discussions touching the very surface of the topic (Flamm and Kaufmann, 2006; Perchoux et al., 2013; Wei et al., 2018), we attempted to investigate centricity more deeply as an additional dimension to the activity spaces. In this line, the present study provided a conceptual and working definition of centricity and presented it as a measurable characteristic of activity spaces. Furthermore, we provided an operational method of measuring centricity and presented a classification of activity spaces based on their level of centricity.

As a major part of daily life, people travel to different locations spread across their activity spaces to engage in activities of different kind. Our study results show that these activity places may form one or more clusters anywhere within one’s activity space, with higher concentration of more frequently visited places in areas nearer to one’s place of residence. These findings are in line with earlier studies predicting formation of activity clusters around daily anchor points, with higher intensity of activities in home vicinity, as the primary life center (Flamm and Kaufmann, 2006; Perchoux et al., 2013). According to the study results, monocentric activity spaces are the most common type followed by bicentric and polycentric activity spaces. One possible explanation of the dominance of monocentric activity spaces in this study can be the age group. Many people belonging to the age group 55–75 may already be retired and thus have fewer daily anchor points. However, this needs to be further examined in a comparative study as the regression results did not reveal any significant association between retirement and centricity.

Expectably, the areas of activity spaces, measured as the surface of the minimum bounding convex polygon, varied significantly between different centricity types. Accordingly, individuals with all activities concentrated around their homes – monocentric, were identified with the smallest activity space area, and individuals with a bigger number of activity clusters, namely bicentric and polycentric, were in turn identified with larger areas of activity spaces. This also emerged as a positive correlation between area, perimeter, mean distance to activity points, and centricity, as different measures of activity space dispersion. Despite the statistical significance, the relatively small correlation coefficients suggest that different measures of dispersion do not precisely capture the same information related to the distribution of activity places. Interestingly, centricity negatively correlated with elongation (insignificant) and Gravelius index (significant). This suggests that centricity captures a different pattern in spatial distribution than in such measures of dispersion. In fact, a higher number of activity clusters is likely to result in a more balanced shape of activity space and thus negatively affect orientation and shape-sensitive measures of activity dispersion.

Despite the overall dominance of monocentric activity spaces, a considerable share of study participants were identified with bicentric and polycentric activity spaces. This indicates that a considerable number of individuals regularly travel to destinations far from their residential environment. Among these, there is a significant share of people identified with polycentric activity spaces suggesting that more than three anchor points may manifest in the individuals’ travel behavior. This means that, in addition to the widely-discussed residential and work/study anchor points, there can be other centers of activities which are harder to directly measure. These other activity centers, which may be formed for a wide range of personal, family-related, and environmental reasons, can be identified through a direct analysis of activity points regardless of presence of any knowledge about physical anchor points.

Our results revealed that none of the socio-economic variables included in this study are statistically significantly associated with centricity of activity spaces. On the other hand, the residential location of individuals in the region was found to be significantly contributing to their centricity of activity spaces. This is in line with a number of previous studies reporting associations between urban form and

<table>
<thead>
<tr>
<th>Visiting areas…</th>
<th>Percent</th>
<th>$\chi^2$ (df = 1, N = 308)</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Denser than home range</td>
<td>62%</td>
<td>10.05</td>
<td>0.005</td>
</tr>
<tr>
<td>Greener than home range</td>
<td>28%</td>
<td>22.01</td>
<td>0.000</td>
</tr>
<tr>
<td>With more water access</td>
<td>27%</td>
<td>20.27</td>
<td>0.000</td>
</tr>
</tbody>
</table>
different characteristics of activity spaces (e.g. Schönfelder and Axhausen, 2002; Perchoux et al., 2014). People inhabiting suburban areas are more likely to have multiple clusters of regular activity places compared to those who live in more densely populated and centrally located areas. These observations can be explained by the urban morphology of suburbs—with lower street connectivity and lower density of services – that forces suburbanites to travel longer distances to visit destinations outside their home range area (Perchoux et al., 2014). Furthermore, our results also show associations between centrality of activity space and choice of transportation mode. People who do most of their activities within their home ranges – monocentric activity space, have reported a considerably higher use of active transportation modes compared to individuals with polycentric activity spaces.

Furthermore, our comparison of urban structure at home vicinity and the extra neighborhood activity clusters of individuals indicated that urban form is seemingly one of the main motivational factors for extra-neighborhood trips. According to our results, the majority of these trips in Helsinki metropolitan are made to destinations with a higher population density compared to the individuals’ own residential environment. In turn, visited areas are in most cases less green than the participants’ neighborhoods, casting doubt on ‘seeking green areas’ as a common incentive for extra-neighborhood travels in Helsinki region. Similarly, visiting water areas did not appear to be a major motivation for extra-neighborhood trips. These findings suggest that in this study area and in this age group, compensatory behaviors other than those classically defined by compensation hypothesis may be at play. Whether for mandatory purposes such as visiting work, or for recreational ones, such as shopping or use of urban amenities, a large proportion of people identified with bicentric and polycentric activity spaces appear to seek areas which are of more urban characteristics than their own residential environments.

Given the observed significance of urban form in centrality of activity spaces and the travel behavior of individuals in general, the results from this study can be particularly interesting to researchers and practitioners studying urban structure and its association with sustainable travel behavior and active living. However, the empirical findings of this study have limitations that need to be addressed in future research. This study is carried out on a dataset collected from senior citizens between 55 and 75 years of age only. The age-specific characteristics of people in this group probably have major impacts on the results. Characteristics such as retirement as well as possible health and activity related restrictions may have significantly contributed to the predominantly small and monocentric characteristic of activity spaces in this study. Future research can benefit from a wider age range where comparisons of activity space characteristics between different age groups are possible.

Furthermore, there are limitations related to the data collection method and the operationalization of centrality that can be improved in future research. This study used a map-based survey to collect data. Individual differences in engagement in mapping among participants as well as differences in their level of mapping skills, may have introduced some biases to the study (Brown, 2016). Furthermore, the dataset used in this study did not include any information on any daily anchor points, other than place of residence. Future research can benefit from a more comprehensive dataset comprising information on various anchor points. This information can enable a comparison of daily life centers with identified activity clusters and add to our understanding of the nature and essence of extra-neighborhood activity clusters. Moreover, the measurement of centrality in this study can also benefit from a richer spatial data with more points. Using richer spatial datasets, such as the ones collected through mobile phone tracking or GPS, can enable the implementation of integrative and more advanced clustering algorithms. This can improve the quality of clustering analysis and potentially help discover additional activity clusters.

Overall, the results from this study show that studying centrality of activity spaces can bring new insights into individual travel behavior. Centricity, in contrast to other existing measures, not only provides us with a quantitative assessment of an activity space’s overall dispersion, but also provides a geographically delineated understanding of how activity places may cluster. In turn, looking at the clusters of activities and classifying activity spaces based on their centrivity can provide us with a bigger picture of the distribution of individual activity spaces and help us scrutinize their underlying personal, socio-economical, and environmental factors. However, future research is needed to deepen our understanding of centrivity and improve our ways of measuring it. A deeper understanding of centrivity can facilitate a transition into a node-edge approach in studying activity spaces in future research. This can empower the analysis of travel behavior by facilitating the use of graph theory analysis resulting in a more comprehensive understanding of activity spaces.

5. Conclusion

Travel behavior, and activity space as a common way of measuring it, are gaining more and more scholarly interest by researchers coming from different fields. Different measures have been developed and various dimensions have been explored to try to better understand these complicated constructs. In this paper we scrutinized the notion of centrivity of activity spaces and examined how people may form clusters of activity points as a result of their daily mobility. Accordingly, we categorized activity spaces into three groups of monocentric, bicentric, and polycentric, and investigated their associations with background variables, urban form, and use of active or motorized travel modes.

The results show that monocentric activity spaces are by far the most common type among senior citizens of Helsinki metropolitan area. However, there is still a considerable share of extra-neighborhood travels that are regularly made, often to denser areas of more urban characteristics. Furthermore, the results show that urban form, but not any of the socio-economic variables, is significantly associated with centrivity of individual activity spaces. However, future research is needed to elucidate the reported associations and investigate other possible dimensions of the observed travel behaviors.

The empirical findings from this study can be useful to researchers and practitioners active in fields of planning, transportation, and contribute to public health policies and interventions promoting healthy and sustainable travel behavior. However, we believe that the greatest contribution of this study is a methodological one. The present study introduced centrivity as a useful measure of activity spaces. Furthermore, this study proposed a method of measuring centrivity and demonstrated its usability with an empirical study. Nevertheless, this a relatively new area of research and more research is still needed. Our understanding of centrivity, along with other characteristics of activity spaces, can significantly benefit, both conceptually and methodologically, from future work in these areas.

Acknowledgments

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Appendix A: Socio-demographic characteristics of respondents (N = 1139)

<table>
<thead>
<tr>
<th></th>
<th>Sample (%)</th>
<th>Statistics Finland (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Gender</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>41</td>
<td>45</td>
</tr>
<tr>
<td>Female</td>
<td>59</td>
<td>55</td>
</tr>
<tr>
<td><strong>Age</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>55–64</td>
<td>51</td>
<td>55</td>
</tr>
<tr>
<td>65–74</td>
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<td>45</td>
</tr>
<tr>
<td>Retired</td>
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<td>59</td>
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<tr>
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<tr>
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<tr>
<td>Upper secondary education</td>
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<tr>
<td>Lower university degree</td>
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</tr>
<tr>
<td>Higher university degree</td>
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<td>17</td>
</tr>
<tr>
<td><strong>Marital status</strong></td>
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<td></td>
</tr>
<tr>
<td>Married</td>
<td>64</td>
<td>55</td>
</tr>
<tr>
<td>Unmarried</td>
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<td>17</td>
</tr>
<tr>
<td>Divorced</td>
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<td>23</td>
</tr>
<tr>
<td>Widow</td>
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<td>6</td>
</tr>
<tr>
<td><strong>Living arrangement</strong></td>
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<td></td>
</tr>
<tr>
<td>Couple</td>
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<td>60</td>
</tr>
<tr>
<td>Living alone</td>
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<td>35</td>
</tr>
<tr>
<td>Other</td>
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<td>5</td>
</tr>
<tr>
<td><strong>Housing</strong></td>
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<td></td>
</tr>
<tr>
<td>Apartment</td>
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<td>70</td>
</tr>
<tr>
<td>Row house apartment</td>
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<td>10</td>
</tr>
<tr>
<td>Detached house</td>
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<td>19</td>
</tr>
<tr>
<td><strong>Mother tongue</strong></td>
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<tr>
<td>Finnish</td>
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<tr>
<td>Swedish</td>
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<td>7</td>
</tr>
<tr>
<td>Other</td>
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<td>6</td>
</tr>
<tr>
<td><strong>Income (median)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ages 55–64</td>
<td>3501–4000</td>
<td>4001–4500</td>
</tr>
<tr>
<td>Ages 65–74</td>
<td>3001–3500</td>
<td>3001–3500</td>
</tr>
</tbody>
</table>

*The sample consists of Finnish people living in the capital area, aged 55–75 in year 2015 (a and b exceptions).

*The reference sample consists of Finnish people living in the capital area, aged 55+ in year 2014.

*The reference sample consists of all the Finnish people aged 55–75 in year 2014.

The bolded variables show statistically significantly different values between sample and population (p < .05).

Appendix B: Calculating Elongation and Gravelius index

\[
\text{Gravelius index (G)} = \frac{P}{2\sqrt{A}}
\]

\[
\text{Elongation (E)} = \frac{b}{a}
\]

- \(P\): MCP's perimeter
- \(A\): MCP's area
- Minimum convex polygon (MCP)
- Minimum fitting rectangle
- Mapped points (home and activity)
References


