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# Examining the effects of residential location and stated residential preferences on activity space size and centrality

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## Abstract

Activity spaces are used to capture patterns in urban mobility and to portray the spatial distribution of day-to-day activities. The literature exploring variation in individual activity spaces identifies strong associations between several activity space characteristics and the built environment of the residential location. This cross-sectional study adds to this evidence by examining whether these associations persist after adjusting for residential self-selection. Adults' everyday mobility was studied using public participation GIS, a participatory mapping method allowing the large-scale collection of laymen-produced spatial data. Activity spaces were defined with a customized minimum convex polygon modelled on the respondents' frequently visited locations. We used linear regression and multinomial logistic regression analyses to study the associations between residential preferences, residential location, and activity space size and centrality. According to our results, residential location significantly influences activity space size and polycentricity in models adjusted for stated residential preferences and individual-level covariates.

## Keywords

Activity space, built environment, residential preference, residential self-selection, polycentricity

## 1. Introduction

Travel behavior studies focusing on the relationship between urban form and individual mobility generally employ descriptives of travel events, such as trip distance and frequency, travel mode choice, or summary measures of travel distances (Næss, 2012). While these outcomes capture information on the travel event, they lack the ability to portray patterns and relations in spatial behavior. Consequently, drawing on space-time geography, some travel behavior studies have incorporated measures of individual activity space to better capture the spatiality of everyday life. As a geographic and spatial indicator, activity spaces are employed to portray individual travel patterns and the spatial distribution of daily activities (Patterson and Farber, 2015; Rai et al., 2007; Schönfelder and Axhausen, 2010). Activity space measures can be used to supplement standard one-dimensional travel behavior estimates with the additional dimensions of spatial and temporal variation (Patterson and Farber, 2015). For these characteristics, the concept of activity space has been growingly used in a range of disciplines besides transportation research, such as urban studies, health geography, epidemiology, and environmental psychology (Kestens et al., 2018; Perchoux et al., 2013; Villanueva et al., 2012; Wang and Li, 2016; Hasanzadeh, 2019a).

Prior research provides consistent evidence of the association between residential location and certain activity space characteristics. Within travel behavior studies, evidence of the longer travel distances of individuals living in suburban rather than in urban settings is generally accepted (Ewing and Cervero, 2001; Næss, 2011; Schwanen and Mokhtarian, 2005a). These differences are generally attributed to shorter destination-distances in central urban areas, which are a product of high destination availability and good street connectivity (Ewing and Cervero, 2001). Results from previous activity space studies focusing on associations between the characteristics of the individual activity space and residential location generally support these assumptions. Compared to suburban areas, residential location in inner urban areas is associated with a decrease in activity space size (Harding et al., 2012; Perchoux et al., 2014; Schönfelder and Axhausen, 2003) and the centering of activity spaces around the place of residence (Hasanzadeh, 2019a, 2019b; Perchoux et al., 2014). These results suggest a strong association between the spatial distribution of everyday activities and the urban form.

However, evidence from travel behavior studies incorporating a wider range of individual-level variables suggests that besides the built environment, individual residential and travel preferences likewise impact travel behavior and mode choice (Acker et al., 2011; Bagley and Mokhtarian, 2002; Kitamura et al., 1997). The effect of residential preferences on the actualized travel behavior has been studied particularly in relation to residential self-selection, i.e., the proposed tendency of residents to seek housing in areas that support their pre-existing travel and land-use preferences (Cao et al., 2009;

De Vos et al., 2018; Handy et al., 2006; van Wee, 2009). Such research addressing the self-selection problem suggests that studying the effect of built environment on travel behavior without controlling for residential self-selection in the form of travel- and land-use preferences may result in the over- or under-estimation of the studied environmental associations. However, while some studies have observed residential self-selection to have a modest, but significant effect and encourage the addition of residential preferences in models predicting travel behavior (Cao et al., 2009), others propose that the effect of self-selection on travel behavior is exaggerated (Næss, 2014).

To the best of our knowledge, no studies to date have examined how either residential self-selection or residential preferences affect the extent and characteristics of activity spaces. Evidence from travel behavior studies suggests that individual travel and land-use preferences affect travel behavior within the limits of the available travel mode and destination options (De Vos et al., 2012; Kamruzzaman et al., 2016; Schwanen and Mokhtarian, 2005b). The expected direction of this effect is that the stated preference towards accessible and compact residential areas with short destination distances results in shorter trip distances and an increase in the use of active and public transportation modes compared to the preference for car-dependent, suburban developments (De Vos et al., 2012; Schwanen & Mokhtarian, 2005b). Based on these results from studies focusing on trip distance and travel mode choice, we hypothesize that residential preferences favoring active transportation modes and short destination distances would similarly result in a decrease in the activity space size and the concentration of travel destinations around the residential location. Detection of a clear self-selection bias would support the inclusion of a control variable in models examining how the built environment explains variation in activity space characteristics.

This paper addresses the above-mentioned gaps in the research by examining the influence of personal-level variables and the built environment on common activity space measures. We apply a public participation GIS (PPGIS) method to combine spatial, behavioral, and attitudinal data and proceed to analyze the joint effect of residential preferences and residential location on activity space characteristics in the context of adults' day-to-day travel. Data on individual residential preferences were used to identify distinct residential preference profiles. Specifically, this study aims to investigate

- 1) The separate associations between activity space size and centrality, residential location, and stated residential preferences (we apply a measure of *activity space centrality* developed by Hasanzadeh (2019b) to identify mono-, bi-, and polycentric activity spaces based on the number of destination clusters),
- 2) The joint associations between the above-mentioned outcome variables, residential location, and residential preferences to examine the effect of residential self-selection.

## 2. Methods

### 2.1. Data collection and methodology

Data on individual mobility patterns were collected using public participation GIS (PPGIS), a digital participatory mapping method enabling the mapping of laymen participants' everyday experiences. PPGIS methods are an efficient way of collecting user-generated spatial data that can be further analyzed and combined with other spatial data sources in GIS (Brown and Kyttä, 2014). The PPGIS survey applied in this study combined survey elements on personal characteristics and attitudinal statements with several mapping tasks concerning the respondent's spatial behavior in day-to-day life.

The data collection was performed in August 2012 in Tampere, Finland. With a population of approximately 238,000 inhabitants (OSF, 2019), Tampere is the third-largest municipality in Finland and a part of the country's second largest urban area. The home addresses of 20,235 randomly sampled inhabitants aged 15 to 74 years were obtained from the Finnish Population Register Centre. A personal invitation to participate in the survey was sent by mail to their home address. Altogether 3,403 respondents participated in the survey. For the purpose of this study, only respondents who provided full answers to the residential preference items and adequate spatial data on their everyday mobility were included. These criteria reduced the final sample to 900 respondents. Compared to municipal-level demographic data (OSF 2012), respondents aged 25 to 39 years were slightly over-represented (38% of participants, 30% of population aged 15 to 74 years in the study area), as were female participants (57% of participants, 51% in the study area).

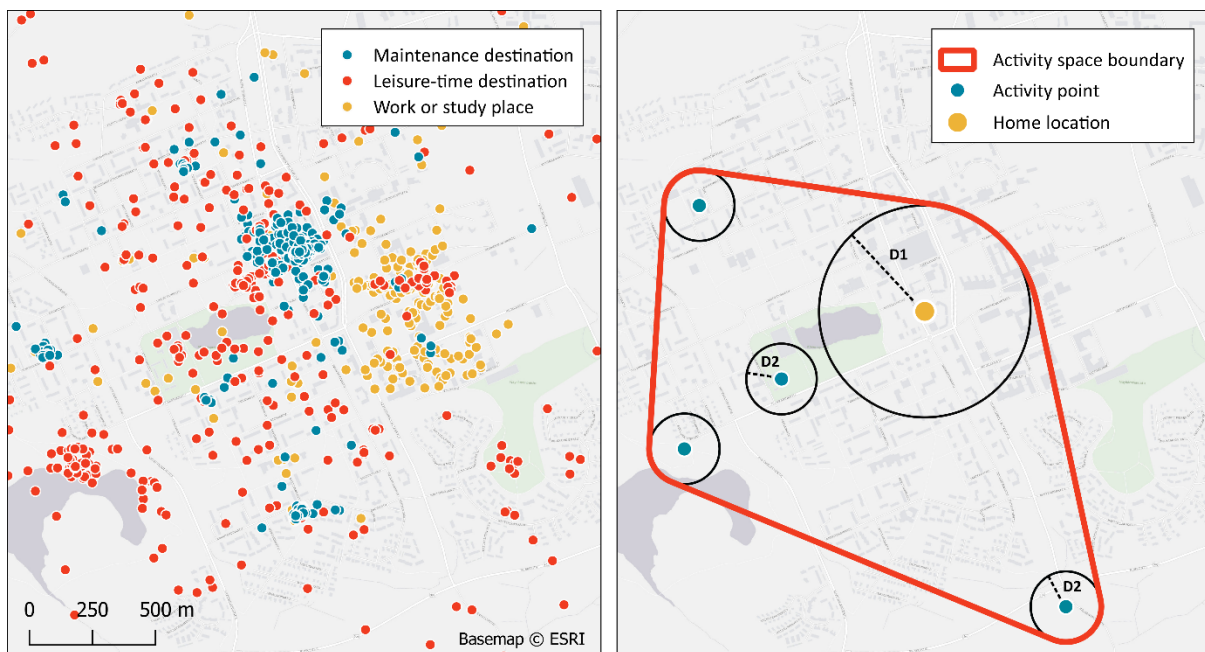
### 2.2. Measures

#### 2.2.1. Individual activity space

The respondents used the survey's mapping view to locate their primary dwelling, work or study place, and other local destinations. Following the concept of *personal network of usual places* proposed by Flamm and Kaufmann (2006), the respondents were advised to locate places that they visit most frequently in their day-to-day life. The respondents could choose freely how many and what type of destinations they wished to map. Destination options were classified into *maintenance destinations* including visits to grocery stores and other services, and into *leisure-time destinations* including destinations for exercising, social interaction, and other recreational activities (Figure 1a).

Activity spaces were formed for each individual entering these activity points to the *home range model*, a customized minimum convex polygon (Figure 1b) that is defined using two buffer distances and a home range distance (Hasanzadeh et al., 2017; Kajosaari et al., 2019). Following Hasanzadeh et al. (2017), buffer distances of 500 m and 140 m were used for home locations and activity points,

respectively. Five hundred meters approximates a typical neighborhood distance that is commonly used in the literature (Berke et al., 2007; Markevych et al., 2016), while 140m was identified as a suitable buffer distance to capture the immediate vicinity of activity points in a comparable dataset (Hasanzadeh et al., 2017). The models were created using the IASM GIS toolbox (Hasanzadeh, 2018). Using the same toolbox, 4.7 km was identified as the optimum home range cut-off distance. This distance was determined with the Jenk's optimization method as the first natural break in the data encompassing more than 80% of the activity points (Hasanzadeh et al., 2017). Consequently, points exceeding this home range cut-off distance were excluded from the analysis. This procedure ensures that activity spaces remain comparable in size by excluding distant and potentially irrelevant points from the data, such as second homes and summer houses located in other municipalities.



**Figure 1 a)** Distribution of activity points in the district of Hervanta, Tampere. **b)** Example of an individual activity space (illustration, not based on response data) and formation of activity space boundaries. D1: Buffer distance for home location (500m). D2: Buffer distance for activity points (140m).

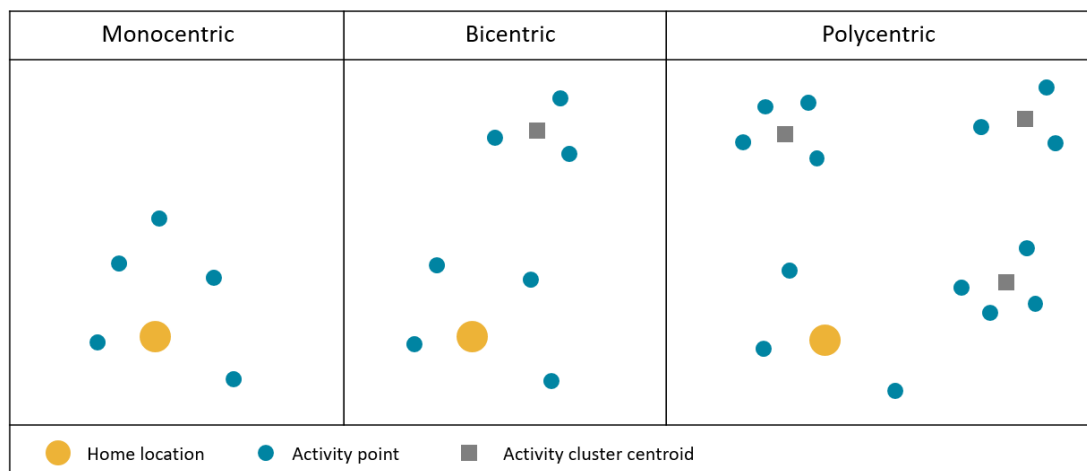
### 2.2.2. Activity space measures

A wide variety of measures are used to describe the characteristics of activity spaces and related geographical concepts (see Hasanzadeh, 2019b and Perchoux et al., 2014 for a detailed discussion). Among the common geometric measures, activity space area and perimeter have been employed in a number of studies to capture the extent of individual mobility and the geographical dispersion of daily activities (Perchoux et al., 2014; Sherman et al., 2005). While such geometric measures provide useful

information on the spatial relations of individual mobility, they do not portray the inner heterogeneity of the activity space (Wei et al., 2018). Therefore, an additional measure of activity space centrality was employed in this study. Centrality of activity space was measured based on the operational definition proposed by Hasanzadeh (2019b). Accordingly, centrality was measured as an ordinal variable of activity space capturing the multiplicity of activity centers in the individual's activity space. The activity clusters were identified using a spatial clustering analysis ensuring that each cluster consists of at least two points and each point was visited at least once a week by the individual (Hasanzadeh 2019b). A distance constraint of 1 km from the cluster centroid was added to the cluster analysis to ensure that the identified clusters remained within a reasonable size and that visits to separate points within a cluster could be connected using active transportation modes.

Consequently, the following activity space measures were used as outcome variables:

- *Area* (in square meters) and *perimeter* (in meters) of the customized minimum convex polygon as measures of activity space size
- *Activity space centrality* following Hasanzadeh (2019b), resulting in a classification of three distinct activity space types (Figure 2). *Monocentric* activity spaces consist of a single cluster of activity places located in home surrounding. *Bicentric* activity spaces consist of another activity center in addition to the cluster of activities around the home. *Polycentric* activity spaces consist of at least two more activity centers in addition to the cluster of activities around the place of residence.



**Figure 2.** A schematic representation of the three activity space centrality measures (modified from Hasanzadeh 2019b).

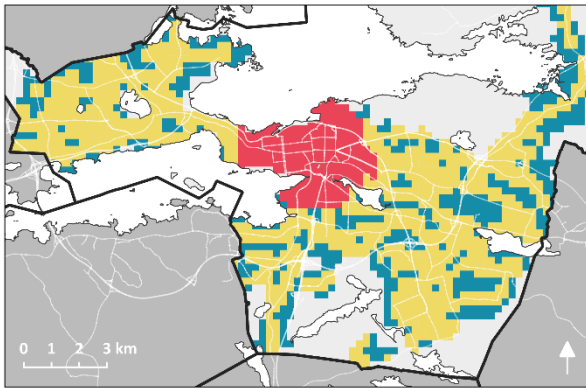
### 2.2.3. Residential location

The relative location within the urban area was defined using categories of travel-related urban zones, a classification available as a 250 m times 250 m grid spanning all Finnish urban areas. The classification is produced and maintained by the Finnish Environmental Institute SYKE (Söderström et al., 2015; SYKE 2015). Within the Tampere region, the classification consists of the following zones: 1) the central pedestrian zone, 2) the fringe of the central pedestrian zone, 3) the pedestrian zones of a sub-center 4), the intensive public transportation zone, 5) the basic public transportation zone, and 6) the car zone. Pedestrian zones are defined by distance to the main central business district (CBD) of the urban region, which in the Tampere region is located in the CBD of Tampere. The central pedestrian zone extends 1.5 km from the CBD. Fringe of the central pedestrian zone includes grid cells with high areal density located within 1 km from the edge of the central pedestrian zone. Public transportation zones mark urban areas, where public transportation provides a competitive option for private vehicle use. Intensive and basic public transportation zones are defined by the availability of public transportation options during rush hours and walking distances to public transportation stops. In Tampere, the intensive public transportation zone differs from the basic public transportation zone by a maximum of 10-minute waiting time compared to the 30-minute waiting time of the basic public transportation zone. In both zones, the maximum walking distance to the nearest public transportation stop is 250 meters. The car zone consists of the remaining urban areas that do not fit the requirements of the pedestrian or the public transportation zones (SYKE 2015).

For the purpose of this study, the travel-related urban zones were merged into three main categories (Figure 3); the central pedestrian zone (zones 1, 2), the public transportation zone (zones 3, 4, 5), and the car zone (zone 6). Respondents were assigned to an urban zone based on their residential location. 32.5% of the respondents lived in the central pedestrian zone, 56.8% in the public transportation zone and 10.7% in the car zone.

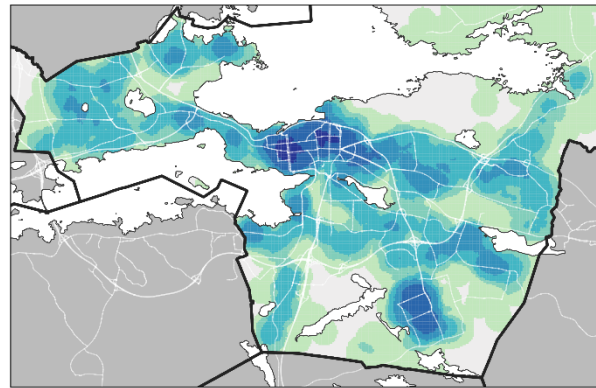


a) Travel-related urban zones and main road network



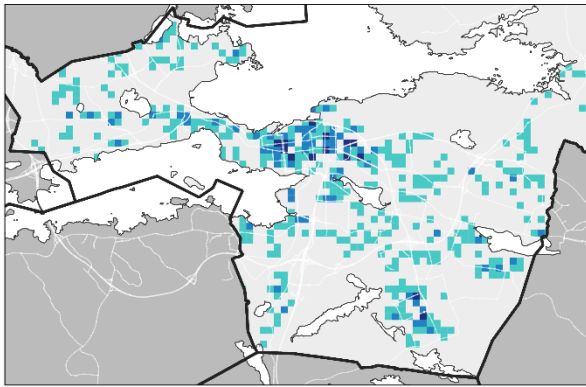
■ Central pedestrian zone    ■ Public transportation zone    ■ Car zone  
 Municipal borders

b) Residential floor area (m<sup>2</sup>) within a 500m buffer distance



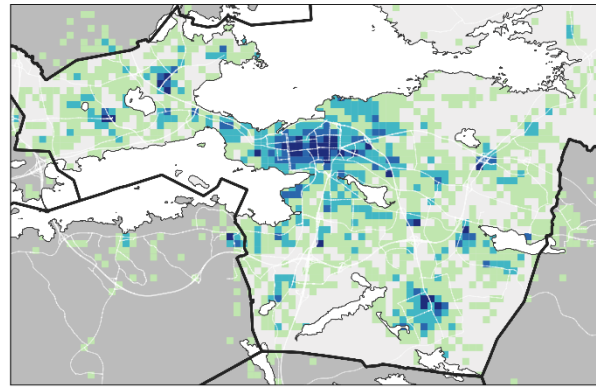
■ 25 - 25,000    ■ 50,001 - 100,000    ■ 200,001 - 400,000  
■ 25,001 - 50,000    ■ 100,001 - 200,000    ■ 400,001 - 650,000

c) Number of respondent home locations within a 250m x 250m grid



■ 1-2    ■ 3-5    ■ 6-16

d) Number of activity points within a 250m x 250m grid



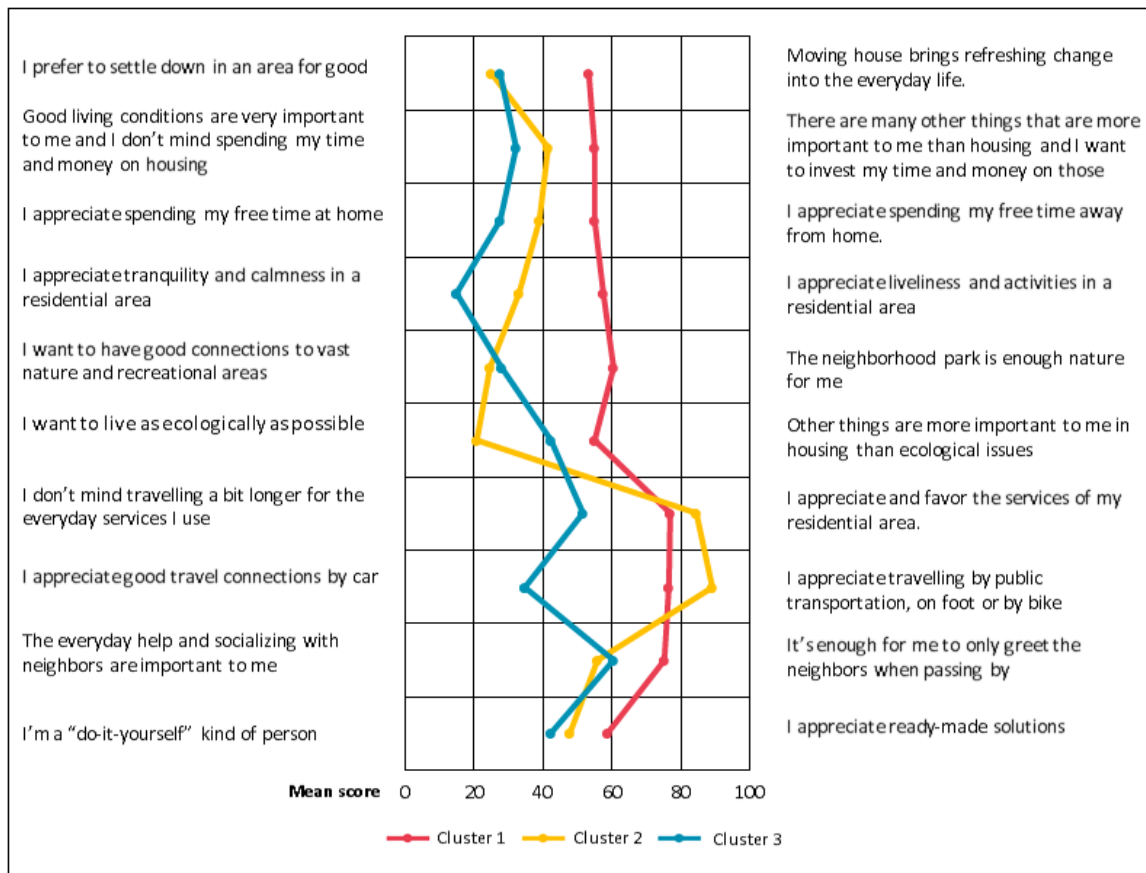
■ 1-5    ■ 6-25    ■ 26-75    ■ 76-350

**Figure 3.** Visualizations of the travel-related urban zones (SYKE, 2015), residential floor area, distribution of respondents' residential locations, and respondent-mapped activity points in the study area.

#### 2.2.4. Residential preference

Residential preferences were measured by ten pairs of attitudinal statements derived from a set of residential preferences identified in previous Finnish studies (Kytta et al., 2010). The paired items measured preferences concerning certain urban built environment characteristics, such as traffic arrangements, service provision, and green infrastructure, while also reflecting individual preferences for the degree of neighboring, commitment to a neighborhood, and willingness to invest in housing (Figure 4). The respondents were asked to state their agreement with the paired statements using a slider with values from 0 to 100 in a trade-off scenario. An exploratory factor analysis of the residential preferences measure in another study (Haybatollahi et al., 2015) showed that each of the attitudinal statements contributed strongly to the overall measure of residential preferences. Therefore, we used the overall score for this measure in our cluster analysis.

Hierarchical cluster analysis with Ward’s method and squared Euclidean distance was used to group the respondents’ based on their scores on the trade-off items. In order to find the optimum number of clusters, we used an agglomeration schedule to compare the coefficient associated with the first solution to a latter one. The comparisons revealed that a three-cluster solution would better distinguish between cases than a four-cluster one, hence three clusters were retrieved. With these results, we were able to clearly identify two clusters with high (Cluster 1) and low (Cluster 3) mean scores on the trade-off items, and a cluster sharing scores on certain items with both of the previous groups (Cluster 2).



**Figure 4.** Mean scores of the residential preference clusters on the residential preference trade-off items.

The retrieved clusters were interpreted based on their mean scores on the attitudinal items (Figure 4). On average, Cluster 1 members prefer lively and active residential environments and like to spend their free time away from home. In their daily life, they favor close-by services that can be reached by active and public transportation. They show less attachment towards their current housing solution than members of the other clusters. Respondents with Cluster 2 membership remind Cluster 1 members by favoring active and public transportation modes and close-by services. However, they differ from the first cluster by willingness to settle down and by appreciating tranquil residential areas that are well

connected to nature and recreational areas. On average, Cluster 2 members are most likely to consider the sustainability of their housing choices. Cluster 3 members remind Cluster 2 members by seeking stability in housing, appreciating good access to recreational areas. On the contrary to Cluster 2 members, they value environments supporting private vehicle use and are willing to travel further to reach their everyday services. Tranquility of the residential environment is more important to them, and they prefer to spend free time at home. Cluster 3 is treated as the reference category, as it differs most from the mobility preferences of the other two clusters.

Chi-square tests on the respondents' socio-demographic background characteristics revealed several significant in-group differences between the three residential preference clusters (Table 1). Cluster 1 members were on average younger and lived more often alone, while Cluster 3 members were on average older, often lived with a partner or with children and were more likely to be fully employed. Although women were overrepresented in the sample, the majority of Cluster 3 members were male. Evidence from residential preference studies posits, that on sample level, a certain congruency is expected between the preferred and the actualized residential environments (e.g. Jansen, 2014). This is also implied by the distribution of cluster members within the travel-related urban zones. The share of respondents living in the central pedestrian zone was highest among Cluster 1 members (45.5%), while Cluster 3 comprised the highest share of respondents living in the car-dependent zone (18.8%).

	Total	Cluster 1	Cluster 2	Cluster 3
	<i>N</i> = 900	<i>n</i> = 225	<i>n</i> = 387	<i>n</i> = 288
<i>Gender (%)</i>				
Female	57.1	56.6	66.5	45.1
Male	42.9	43.4	33.5	54.9
<i>Age, years (%)</i>				
16-24	17.7	31.6	14.4	12.1
25-39	38.0	34.7	43.7	32.8
40-64	34.9	28.5	33.0	41.9
65-75	9.4	5.2	8.9	13.2
<i>Employment status (%)</i>				
Employed	53.2	43.9	52.0	61.8
Unemployed	5.0	6.6	5.4	3.4
Retired	14.4	10.6	13.9	18.0
Student	21.7	32.8	22.4	12.4
Other	5.6	6.0	6.3	4.4
<i>Commuting to work or study place<sup>a</sup></i>				
Yes	54.2	50.2	55.6	55.6
No	45.8	49.8	44.4	44.4
<i>Household type (%)</i>				
Single person	29.8	46.2	27.8	20.2
Couple without children	43.3	28.4	45.5	51.3
Couple with children	20.1	17.8	18.8	23.6
Other	6.8	7.6	7.9	4.9
<i>Residential location (%)</i>				
Central pedestrian zone	32.5	45.5	37.5	15.2
Public transportation zone	56.8	50.0	54.0	66.1
Car zone	10.7	4.5	8.5	18.8

Note: Chi-square tests were used to assess differences in group means between the residential preference clusters. In-group differences were significant ( $p < .001$ ) on all variables but commuting to work or study place ( $p = .380$ ).

<sup>a</sup> Including respondents commuting at least once a week to a work or study place located further than 1 km from home.

**Table 1.** Personal characteristics by residential preference cluster

### 2.2.5. Control variables

Certain socio-economic and demographic characteristics have been associated with variation in activity space measures. Perchoux et al. (2014) observed that males had significantly larger activity spaces than females, and that being full-time employed significantly increased the activity space size. Hasanzadeh et al. (2019b) reported that a decrease in respondent age and living in a household with children

increased the likelihood of having a polycentric activity space. As the work place is a common secondary node for the daily activities to cluster around (Rainham et al., 2010; Perchoux et al., 2013), we assessed the effect of a work place located outside the neighborhood on the activity space measures. Thus, commuting behavior was dichotomized as commuting or not commuting at least once a week to a work or study place located further than 1 km from home. Consequently, all models were adjusted for gender, age, employment status, household type, and commuting behavior. Additionally, models were adjusted for the total number of destinations mapped by the respondent in order to ensure that variation in activity space characteristics was not caused by differences in mapping activity.

### **2.3. Data analysis**

Linear and multinomial logistic regression analyses were used to study associations between the stated residential preference, residential location, and the activity space characteristics. The outcome variables included activity space area, perimeter, and a categorical centrality variable. All continuous dependent variables were log-transformed (LG10) to approximate a normal distribution. Data were checked and there were no problems with heteroscedasticity or with extreme outliers.

## **3. Results**

### **3.1. Activity space descriptives**

The study participants mapped on average 6.8 activity points (Table 2). Significant in-group differences in the average distances to work ( $H(2) = 73.87, p < .001$ ), maintenance ( $H(2) = 159.67, p < .001$ ), and leisure-time destinations ( $H(2) = 35.99, p < .001$ ) were observed between respondents living in different travel-related urban zones. Likewise, significant differences existed between the residential preference clusters in the average distances to work ( $H(2) = 17.87, p < .001$ ), maintenance ( $H(2) = 56.02, p < .001$ ), and leisure-time destinations ( $H(2) = 14.43, p = .001$ ).

Monocentric activity space was the most common activity space type identified with 53.7% of the respondents (Table 2). 24.9% of the respondents had bicentric and 21.4% polycentric activity spaces. There were significant in-group differences in activity space area ( $H(2) = 14.10, p = .001$ ) and perimeter ( $H(2) = 21.09, p < .001$ ) between respondents living in different urban zones. The residential preference clusters differed significantly only in activity space perimeter ( $H(2) = 6.78, p = .034$ ). Activity space centrality differed by both residential location ( $\chi^2 = 36.47, p < .001$ ) and the residential preference cluster ( $\chi^2 = 13.12, p = .011$ ). Monocentric activity spaces were more common amongst respondents living in central areas, whereas the share of respondents with a polycentric activity space was highest amongst those living in car-dependent areas. Among the residential preference cluster, Cluster 1

members had the highest share of monocentric (60.4%) and Cluster 3 members the highest share of polycentric (26.4%) activity spaces.

On the sample level, significant differences existed in the area ( $H(2) = 34.08, p < .001$ ) and perimeter ( $H(2) = 39.86, p < .001$ ) of different activity space types. As expected, monocentric activity spaces were on average significantly smaller in size than bicentric and polycentric activity spaces. Likewise, the average number of activity points was higher for bi- and polycentric (6.7 and 10.4 activity points, respectively) than monocentric activity spaces (5.7 activity points).

	Total	Residential location			p-value	Residential preference			p-value
		Central pedestrian zone	Public transportation zone	Car zone		Cluster 1	Cluster 2	Cluster 3	
	N = 900	n = 289	n = 504	n = 95		n = 225	n = 387	n = 288	
<i>Activity space size</i>									
Area (km <sup>2</sup> )	3.9	3.5	4.0	5.3	0.001	3.5	4.1	4.1	0.081
Perimeter (km)	8.2	7.7	8.3	9.9	< 0.001	7.6	8.4	8.4	0.034
<i>Centricity of activity space</i>									
Monocentric	53.7	65.4	49.4	47.4	< 0.001	60.4	54.3	47.6	0.011
Bicentric	24.9	24.9	25.2	22.1		25.3	23.8	26.0	
Polycentric	21.4	9.7	25.4	30.5		14.2	22.0	26.4	
<i>Average distance to destinations (km)</i>									
Work or study places	3.4	2.2	3.8	4.8	< 0.001	3.0	3.2	4.1	< 0.001
Maintenance destinations	1.2	0.8	1.4	1.8	< 0.001	1.0	1.1	1.6	< 0.001
Leisure-time destinations	3.3	2.5	3.7	4.1	< 0.001	3.3	2.9	4.2	0.001
<i>Main travel mode to activity points<sup>a</sup></i>									
Active transportation	51.8	70.6	43.5	33.4	< 0.001	55.9	61.6	32.6	< 0.001
Public transportation	12.5	8.3	16.0	7.5		13.7	15.0	7.2	
Private vehicle	18.2	6.5	22.3	35.5		10.8	6.1	44.3	
Varied modes / Other	17.5	14.6	18.2	23.5		19.6	17.3	15.8	
<i>Number of activity points</i>	6.8	7.8	6.4	6.5	0.005	6.9	7.7	5.6	< 0.001

Note: Chi-square and Kruskal-Wallis H tests were used to assess differences in group means.

<sup>a</sup>Weighted by the number of monthly visits to each destination.

**Table 2.** Activity space characteristics by residential location and residential preference cluster

### ***3.2. Activity space size***

Activity space size was measured by area and perimeter. For both variables, three adjusted models were tested. Models 1 and 2 tested separately the effects of residential preference and residential location on outcome variables while controlling for socio-demographic characteristics and the number of mapped locations. Model 3 tested the full model including both of the main predictors. Taking the control variables into account, residential preferences and residential location were significantly associated with both activity space area and perimeter in Models 1 and 2 (Table 3, Table 4). These significant associations persisted in the full model (Model 3) for residential location and partly for residential preferences. Residential location in the car zone or in the public transportation zone significantly increased the activity space area (car zone:  $\beta = 0.18, p < .001$ ; public transportation zone:  $\beta = 0.06, p = .027$ ) and perimeter (car zone:  $\beta = 0.11, p < .001$ ; public transportation zone:  $\beta = 0.03, p = .030$ ). Respondents in Cluster 2 had significantly smaller activity space area ( $\beta = -0.06, p = .030$ ) and activity space perimeter ( $\beta = -0.03, p = .048$ ) than respondents in Cluster 3. In the final model, commuting to a work or study place was positively associated with an increase in both area ( $\beta = 0.10, p < .001$ ) and perimeter ( $\beta = 0.07, p < .001$ ). The final model explained 39% of the total variation in activity space area ( $R^2 = .39, p < .001$ ). As residential location appeared as the stronger predicting variable, we examined whether this predicting effect depended on the respondent's residential preference. Therefore, a moderating effect of residential preference was tested (not shown). The results indicated no significant moderating effect, and thus suggest a universal association between these two variables.

	Model 1		Model 2		Model 3	
	Beta	(95% CI for B)	Beta	(95% CI for B)	Beta	(95% CI for B)
Age	0.01	(0.00, 0.00)	0.00	(0.00, 0.00)	0.00	(0.00, 0.00)
Gender (ref. male)						
<i>Female</i>	-0.03	(-0.07, 0.01)	-0.04	(-0.08, 0.01)	-0.03	(-0.07, 0.01)
Employment (ref. no full-time employment)						
<i>Full-time employment</i>	0.03	(-0.01, 0.07)	0.04	(0.00, 0.08)	0.04	(-0.01, 0.08)
Commuting to work or study place (ref. no) <sup>a</sup>						
<i>Yes</i>	0.10***	(0.06, 0.14)	0.10***	(0.06, 0.14)	0.10***	(0.06, 0.14)
Children in the family (ref. no)						
<i>Yes</i>	0.00	(-0.05, 0.05)	-0.02	(-0.06, 0.03)	-0.02	(-0.07, 0.03)
Number of activity points	0.04***	(0.04, 0.04)	0.04***	(0.04, 0.04)	0.04***	(0.04, 0.04)
Residential preference cluster (ref. Cluster 3)						
<i>Cluster 1</i>	-0.08**	(-0.13, -0.02)			-0.06	(-0.11, 0.00)
<i>Cluster 2</i>	-0.06*	(-0.11, -0.01)			-0.05*	(-0.10, -0.01)
Residential location (ref. central ped. zone)						
<i>Public transportation zone</i>			0.06**	(0.02, 0.11)	0.06*	(0.01, 0.10)
<i>Car zone</i>			0.20***	(0.13, 0.26)	0.18***	(0.11, 0.25)
R <sup>2</sup>	0.36		0.39		0.39	

Model 1 = Residential preference and control variables.

Model 2 = Residential location and control variables.

Model 3 = Residential preference, residential location and control variables.

\*  $p < .05$ , \*\*  $p < .01$ , \*\*\*  $p < .001$ .

CI = Confidence interval.

<sup>a</sup> Including respondents commuting at least once a week to a work or study place located further than 1 km from home.

**Table 3.** Models examining associations between residential preference, residential location, and activity space area



	Model 1		Model 2		Model 3	
	Beta	(95% CI for B)	Beta	(95% CI for B)	Beta	(95% CI for B)
Age	0.00	(0.00, 0.00)	0.00	(0.00, 0.00)	0.00	(0.00, 0.00)
Gender (ref. male)						
<i>Female</i>	-0.02	(-0.04, 0.01)	-0.02	(-0.05, 0.01)	-0.02	(-0.04, 0.01)
Employment (ref. no full-time employment)						
<i>Full-time employment</i>	0.02	(-0.01, 0.04)	0.02	(-0.01, 0.05)	0.02	(-0.01, 0.05)
Commuting to work or study place (ref. no) <sup>a</sup>						
<i>Yes</i>	0.07***	(0.05, 0.10)	0.07***	(0.05, 0.10)	0.07***	(0.04, 0.10)
Children in the family (ref. no)						
<i>Yes</i>	0.00	(-0.03, 0.03)	-0.01	(-0.04, 0.02)	-0.01	(-0.04, 0.02)
Number of activity points	0.02***	(0.02, 0.02)	0.02***	(0.02, 0.02)	0.02***	(0.02, 0.02)
Residential preference cluster (ref. Cluster 3)						
<i>Cluster 1</i>	-0.05**	(-0.08, -0.01)			-0.03	(-0.07, 0.00)
<i>Cluster 2</i>	-0.04*	(-0.06, -0.01)			-0.03*	(-0.06, -0.01)
Residential location (ref. central ped. zone)						
<i>Public transportation zone</i>			0.04**	(0.01, 0.07)	0.03*	(0.01, 0.06)
<i>Car zone</i>			0.12***	(0.08, 0.17)	0.11***	(0.07, 0.16)
R <sup>2</sup>	0.29		0.31		0.31	

Model 1 = Residential preference and control variables.

Model 2 = Residential location and control variables.

Model 3 = Residential preference, residential location and control variables.

\*  $p < .05$ , \*\*  $p < .01$ , \*\*\*  $p < .001$ .

CI = Confidence interval.

<sup>a</sup>Including respondents commuting at least once a week to a work or study place located further than 1 km from home.

**Table 4.** Models examining associations between residential preference, residential location and activity space perimeter

	Model 1		Model 2		Model 3	
	OR	(95% CI)	OR	(95% CI)	OR	(95% CI)
<b>Bicentric (ref. monocentric)</b>						
Age	1.01	(1.00, 1.02)	1.01	(1.00, 1.02)	1.01	(0.99, 1.02)
Gender (female, ref. male)	0.63*	(0.43, 0.93)	0.59**	(0.40, 0.86)	0.61*	(0.42, 0.90)
Full-time employment (yes, ref. no)	1.07	(0.72, 1.60)	1.06	(0.71, 1.59)	1.04	(0.69, 1.56)
Commuting to work or study place (yes, ref. no) <sup>a</sup>	5.52***	(3.51, 8.67)	5.59***	(3.55, 8.81)	5.55***	(3.52, 8.76)
Children in the family (yes, ref. no)	0.88	(0.57, 1.37)	0.94	(0.59, 1.48)	0.94	(0.59, 1.49)
Number of activity points	1.11***	(1.06, 1.18)	1.11***	(1.05, 1.17)	1.12***	(1.06, 1.18)
Residential preference (ref. C3)						
<i>Cluster 1</i>	0.80	(0.48, 1.33)			0.83	(0.49, 1.41)
<i>Cluster 2</i>	0.69	(0.44, 1.08)			0.74	(0.47, 1.18)
Residential location (ref. central ped. zone)						
<i>Public transportation zone</i>			1.29	(0.84, 1.98)	1.25	(0.81, 1.93)
<i>Car zone</i>			1.31	(0.65, 2.64)	1.22	(0.60, 2.48)
<b>Polycentric (ref. monocentric)</b>						
Age	1.00	(0.98, 1.01)	0.99	(0.98, 1.01)	0.99	(0.97, 1.01)
Gender (female, ref. male)	0.77	(0.50, 1.19)	0.72	(0.46, 1.12)	0.76	(0.48, 1.21)
Full-time employment (yes, ref. no)	1.33	(0.84, 2.11)	1.44	(0.89, 2.35)	1.36	(0.83, 2.23)
Commuting outside neighborhood (yes, ref. no) <sup>a</sup>	3.49***	(2.13, 5.70)	3.61***	(2.15, 6.07)	3.43***	(2.04, 5.79)
Children in the family (yes, ref. no)	0.99	(0.61, 1.62)	1.28	(0.77, 2.15)	1.32	(0.79, 2.22)
Number of activity points	1.28***	(1.21, 1.35)	1.32***	(1.25, 1.40)	1.33***	(1.26, 1.42)
Residential preference (ref. C3)						
<i>Cluster 1</i>	0.30***	(0.16, 0.56)			0.48*	(0.25, 0.95)
<i>Cluster 2</i>	0.46**	(0.28, 0.75)			0.63	(0.37, 1.07)
Residential location (ref. central ped. zone)						
<i>Public transportation zone</i>			7.46***	(3.85, 14.49)	6.82***	(3.49, 13.31)
<i>Car zone</i>			11.72***	(4.99, 27.49)	9.89***	(4.18, 23.43)
Pseudo R <sup>2</sup> (Nagelkerke)	0.32		0.37		0.37	
Model $\chi^2$	249.20***		290.79***		296.63***	

Model 1 = Residential preference and control variables.

Model 2 = Residential location and control variables.

Model 3 = Residential preference, residential location and control variables.

\*  $p < .05$ , \*\*  $p < .01$ , \*\*\*  $p < .001$ .

OR = Odds ratio, CI = Confidence interval.

<sup>a</sup> Including respondents commuting at least once a week to a work or study place located further than 1 km from home.

**Table 5.** Odds ratios and 95% confidence intervals from models examining associations between activity space centrality, residential location, and residential preference

### **3.3. Activity space centrality**

Three multinomial logistic regression models were tested to examine the impact of residential preferences and the residential location on activity space centrality. The associations between the two independent variables and activity space centrality were tested jointly in Model 3 and separately in Model 1 and Model 2 (Table 5). Model 1 showed a significant decrease in the odds of having a polycentric rather than a monocentric activity space for Cluster 1 (OR = 0.30, CI: 0.16, 0.56) and Cluster 2 members (OR = 0.46, CI: 0.28, 0.75). This association persisted for Cluster 1 (OR = 0.48, CI: 0.25, 0.95) in Model 3 including the residential location. Model 2 revealed strong associations between residential location and the odds of having a polycentric activity space. These associations remained highly significant in Model 3 for both residential location in the public transportation zone (OR = 6.82, CI: 3.49, 13.31) and in the car zone (OR = 9.89, CI: 4.18, 23.43). In addition to residential preferences and the residential location, commuting to work or study place significantly increased the odds of having a bicentric or polycentric activity space in all of the tested models. Being female decreased the odds of having a bicentric rather than a monocentric activity space.

## **4. Discussion**

The results of this study suggest that residential location significantly influences activity space size and the spatial concentration of day-to-day activities. In order to confirm that this association remains significant after controlling for residential self-selection, we examined the associations between stated residential preferences, residential location, and activity space measures. While residential self-selection has been extensively discussed within travel behavior literature (e.g., Cao et al., 2009; De Vos et al., 2018; Handy et al., 2006; van Wee, 2009) the topic has remained largely unaddressed in the activity space literature.

Residential preferences showed significant associations with both activity space size and centrality in the unadjusted models. The observed associations were as hypothesized, as stated preferences towards accessible and compact residential areas with short destination distances resulted in smaller activity spaces with a higher concentration of activities. However, these effects were diminished in the full models including residential location, showing only modest negative associations between residential preferences and the activity space outcomes. As several travel behavior studies have observed varied interactions between the residential preference and the neighborhood type (De Vos et al., 2012; Schwanen and Mokhtarian, 2005b), we tested the possible moderating effects of residential preference on the association between the residential location and activity space size. However, no significant moderating effects were found, thereby suggesting a more complex and possibly non-symmetric relationship between these variables (Guan et al., 2020). While we observed minor decreases in the effect sizes of the associations between the residential location and activity space outcomes after

adjusting for residential preferences, all of the observed associations remained significant. Activity space centrality, in particular, retained a strong and significant ( $p < .001$ ) relationship with the built environment. Based on these results, we conclude that studies examining the relationships between the built environment and activity space characteristics but ignoring residential self-selection might to some extent overestimate the built environment influences. However, considering the strength and significance of these associations, accounting for this overestimation did not change the final results or their interpretation. Evidently, residential location significantly influences the activity space size and the concentration of activities, regardless of possible residential self-selection.

Residential location was significantly associated with activity space size in all final models, accounting for residential preferences, commuting behavior, and socio-demographic covariates. Compared to respondents living in the most centrally located areas, respondents residing in suburban areas were more likely to have larger activity spaces. Consequently, individuals residing in urban settings with high destination availability and good access to public transportation were more likely to have their day-to-day activities concentrated in a smaller geographical area than individuals living in car-dependent neighborhoods, regardless of their travel and land-use preferences. Differences to suburban areas with good public transportation were less significant, suggesting that these areas offer possibilities to reach day-to-day destinations in the relative vicinity of the home. These findings are consistent with prior studies on activity space size (Hasanzadeh et al., 2018; Perchoux et al., 2014; Schönfelder and Axhausen, 2003) and evidence of the shorter travel distances of individuals living in urban rather than in suburban settings (Ewing and Cervero, 2001; Schwanen and Mokhtarian, 2005a). The result that residential location has an independent association with activity space characteristics is likewise supported by results from other Nordic studies on travel distance and travel mode choice in urban contexts (Næss, 2009; Wolday et al., 2019, 2018).

In addition to size, activity spaces can be described with diverse measures representing the concentration of activities within activity spaces or the spatial relations between these activities. In this study, we applied a centrality measure identifying mono-, bi-, and polycentric activity spaces based on the concentration of activities in separate activity clusters. Combined with built environment and personal variables, such measures can help us to better understand how our urban environments create opportunities to lead lives with different mobility preferences, capabilities, and needs. The centrality measure used in this study provides information on the distribution and clustering of travel destinations and is thus well-suited to supplement standard travel event and activity space measures that indicate the extent of mobility. As a spatial research tool, it can support empiric research addressing societal changes in mobilities, such as transport disadvantage (Lucas, 2012) or the mobility needs of ageing populations (Alsnih and Hensher, 2003). In the present study, the majority of the participants (54%) were identified with monocentric activity spaces, i.e. activity spaces where travel destinations are clustered around one

main node. The remaining respondents were identified with either bicentric or polycentric activity spaces indicating the clustering of activities to one or more activity centers outside the residential area.

The centrality measure used in this study describes solely the distribution of activities around multiple activity centers. However, if paired with individual mobility preferences or other personal-level covariates, the centrality measure can be used to identify neighborhood structures with varying levels of resilience towards changes in mobility needs. Regarding polycentric activity spaces, polycentricity among individuals preferring more local lifestyles may indicate that their residential environments provide little opportunities for local living. Similarly, a monocentric activity space can indicate a mobility pattern in which most daily destinations are reached in the neighborhood or its vicinity. As such, this activity space type closely corresponds to the ideals of concepts for local and resilient neighborhoods exemplified by the “15-minute city”. Alternatively, activity space monocentricity can indicate reduced mobility due to the scarcity of accessible destinations, lack of public transport options, or other features of the built, social, or natural environment that may directly or indirectly limit individual mobility. Such interpretation would be possible for individuals with clear disparities between the preferred and actualized daily mobility patterns.

This study confirmed findings of previous studies (Hasanzadeh 2019b; Hasanzadeh et al., 2019) which found a statistically significant association between activity space centrality and the residential location. Our results indicated that living in a car-dependent residential area increased the likelihood of having a polycentric activity space regardless of socio-demographic characteristics, commuting behavior, and residential preferences. By contrast, no significant associations were found between residential location and the likelihood of having a bicentric activity space. Among the control variables, regular commuting to a work or study place located further than 1 km from home was consistently associated with activity space bicentricity. As Perchoux and colleagues (2013) note, the workplace is typically the secondary node that daily activities cluster around. Residents are less likely to have control on their workplace location than on the location of other daily activities, such as shopping for groceries. It is likely that regardless of the built environment characteristics of the residential area, residents need to commute to workplaces located outside their neighborhoods. The participants of this study had, on average, a commute distance of 3.4 km to their main work or study location, while distances to maintenance destinations such as grocery stores and other services were generally shorter, on average 1.2 km.

These results on the centering of everyday activities suggest that while the bicentricity of the activity space is primarily associated with occupational activities, the polycentricity of an activity space is strongly associated with the built environment characteristics of the residential environment. Residents living in central areas that have generally high destination availability and residential density were less likely to have an additional activity cluster, indicating a higher centering of daily activities. By contrast, activity clusters are common amongst residents living in suburban areas, who, due to the urban structure

and destination availability of their residential area, are likely to visit at least the CBD or a secondary urban node with specialized service, shopping, and leisure-time possibilities in addition to their home and work environments (Hasanzadeh, 2019). These findings on the polycentric mobility patterns of respondents living in car-dependent areas provide a spatial context for interpreting the longer travel distances frequently observed among suburban residents (Ewing and Cervero, 2001; Næss, 2011; Schwanen and Mokhtarian, 2005a). Our results suggest that these longer travel distances are not only attributable to the geographic distance to services, but also to the urban structure requiring reliance on the private vehicle and resulting in the distribution of visited destinations in multiple activity centers. The associations between polycentricity and residential location in a car-dependent area remained strong after adjusting for individual preferences, thereby indicating that these areas provide limited possibilities for inhabitants hoping to lead more local and less car-dependent lifestyles.

Although this study approached activity space research from a mobility perspective, these results on activity space centrality have wider applicability in studies focusing on the relationships and causalities between the built environment and specific travel behavioral outcomes, such as the use of active transportation modes. The results on the explicit effect of the residential location on activity space centrality contribute to identifying the actual environmental exposures beyond the immediate residential neighborhood. Better understanding of residential and non-residential exposures is crucial for studies focusing on relationships between built environment and behavioral outcomes in order to avoid individual exposure misclassification (Perchoux et al., 2013).

Lastly, we tested the relationships between several personal-level covariates and the activity space characteristics. However, only commuting behavior and gender shared any significant associations with the studied outcomes. This result diverges from the findings of a number of previous studies showing that variables related to the stage of life, such as age and household structure (Hasanzadeh et al., 2018; Perchoux et al., 2014), are associated with activity space characteristics. The lack of personal-level associations in the present study can be attributed to several reasons. First, respondents with distinct residential preferences and locations differed significantly by several of their socio-demographic characteristics, suggesting that these variables explained also life-stage differences. Further, the sample did not include individuals above 75 years of age, hence excluding an age group that is likely to have mobility difficulties (Sainio et al., 2006).

#### ***4.2. Study limitations***

The present study has certain limitations. First, the results are based on a cross-sectional study design that is unable to infer causality between personal characteristics, environmental context, and travel behavior. Moreover, this study design is not able to account for the possible changes that occur in residential preferences over time. A considerable share of the respondents lived in residential

environments that contradicted their stated preferences. This is a common observation among studies addressing residential dissonance (De Vos et al., 2012; Kajosaari et al., 2019; Schwanen and Mokhtarian, 2005a, 2004), pointing to the many constraints and trade-offs households are required to manage during residential location choice (Næss, 2014). Some evidence exists that individuals living in residential environments that do not correspond to their preferences are likely to gradually adjust their preferences to better match the current living environment (Kamruzzaman et al., 2015; Lin et al., 2017; De Vos et al., 2018). Natural experiments and longitudinal studies measuring travel behavior and environmental attitudes prior to and after a move remain the most promising study settings to address the causalities between built residential environment and travel behavior (Cao et al., 2009; Guan et al., 2020). Second, this study applied a limited number of items measuring residential preferences. These were selected from items featured in Finnish housing studies, and should be taken into account within this context. Furthermore, activity space modelling applied in this study relies on the respondents' self-reported spatial behavior, and may cause biases depending on the level of mapping skills and the respondent's interest towards the mapping task. These differences were minimized in the analyses by adjusting for the total amount of mapped destinations. Lastly, the ways the built environment influences activity space characteristics are likely to vary between different urban contexts. While in Finnish urban areas the built environment appears to have a significant effect on the activity space characteristics regardless of residential self-selection, opposite results might be observed in urban areas with differing morphology or public transportation network. We encourage future research to compare the associations between activity space characteristics and the built environment in diverse urban settings and populations.

## **5. Conclusions**

The increasing availability of spatial behavioral data presents new possibilities for studying mobility using individual activity spaces. These measures portray spatial relations and patterns in travel behavior and can thus be used to capture the extent and distribution of day-to-day activities. This cross-sectional study examined to which extent variation in activity space size and polycentricity is explained by the residential location relative to the urban structure, and whether this effect is attributable to travel-related residential self-selection, i.e. the tendency of residents to seek housing in areas that support their pre-existing travel preferences (Cao et al., 2009; Handy et al., 2006).

The results of this study suggest that residential location has a significant effect on activity space size and polycentricity after controlling for residential preferences and socio-demographic characteristics. Residential preferences retained modest independent associations with activity space outcomes after adjusting for residential location. However, no moderating effect was observed between these variables, suggesting a more complex relationship between personal characteristics, the built environment, and

daily mobility patterns. Overall, our results suggest that while not controlling for residential preferences might lead to a modest over-estimation of the built environment influences, it is evident that residential location influences the activity space size and polycentricity, regardless of residential self-selection.

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## **CRedit authorship contribution statement Anna Kajosaari:**

Conceptualization, Methodology, Formal analysis, Writing - original draft, Writing - review & editing, Visualization. **Sayed M. Haybatollahi:** Formal analysis, Writing - review & editing.

**Kamyar Hasanzadeh:** Methodology, Formal analysis, Writing - original draft, Writing - review & editing. **Marketta Kyttä:** Conceptualization, Investigation, Writing - review & editing.

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