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The sociability space: putting social networks into geographical space

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Abstract

Social interactions and daily mobility are two behaviors that mutually transform throughout life. Understanding how they interact is particularly important for elderly people, who are more at risk to be spatially and socially isolated. From data collected among a sample of 225 people aged 60 and over living in the Paris region (France), we explore how their social interactions are embedded into their activity space using the new concept of “sociability space” (the geographical portion of the activity space consisting of places visited with social network member). Sociability places are found to be less numerous, less diversified, more spatially dispersed and more decentered from residence than non-sociability places. Regarding traditional social network measures (degree, global clustering, etc.), stronger and more numerous correlations are observed with the structural characteristics of sociability spaces than with non-sociability spaces. Finally, variations in structural characteristics of sociability spaces according to people’s socio-demographic and residential profiles largely differ from those observed in structural characteristics of non-sociability spaces. This empirical study shows that “sociability space” indicators are complementary to social network indicators and provide a more precise picture of geography of social interactions than activity space considered as a whole. Such approach may help to identify particular groups at risk of social isolation, such as people living alone and those with a low level of education, and inspire public policies aiming at both promoting daily mobility and reducing social isolation.

Keywords: sociability space, social networks, daily mobility, elderly people, Paris

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1 Introduction

Social networks and daily mobility are part of the interrelated social and geographical contexts that constitute everyday life (Ye & Liu, 2019; Zhao et al., 2019). Social structures shape people's daily activities including their mobility patterns (Chen et al., 2022; Lee & Kwan, 2011; Puura et al., 2022), and play an important role in defining the geographical environments to which people are exposed to (Kestens et al., 2017). Conversely, daily mobility plays an important role in defining the social environments in which people interact and build their social network. The resulting activity space [i.e. the geographical extent in which people move in the course of their daily activities (Golledge & Stimson, 1997)] shapes people's social ability to engage in social interactions.

Although social networks and daily mobility are closely interconnected, measures of social network proposed in the literature are mainly spatially blind and conversely measures of daily mobility are mainly socially blind (Andris, 2016; Andris et al., 2018; Wang et al., 2015; Ye & Liu, 2019). Social network and daily mobility analyses are developed in separate scientific fields and analysed quantitatively using separate methodologies: social network analysis and spatial/geostatistical analysis (Andris & Sarkar, 2022; Wang et al., 2015). Social network measures rarely account for places where people meet members of their social network: family, friends and professional contacts are usually studied from a purely topological perspective considering the position and intensity of nodes and links (Newman, 2010). Similarly, structural measures of daily mobility do not account for social interactions people have in the course of their daily activities. Activity spaces are described from spatial extent and dispersion of activity locations (Hasanzadeh et al., 2018; Lord et al., 2009; Perchoux et al., 2014), but ignore the social interactions occurring in the various activity locations.

Some illustrations of the weak combination between social networks and daily mobility can be found in the public health and epidemiology literature, where these two components are mainly studied as independent determinants of health and wellbeing (Berkman et al., 2014; Berkman & Kawachi, 2000; Kestens et al., 2017; Perkins et al., 2015; K. P. Smith & Christakis, 2008). Social relationships provide several benefits, including social support, exerting social influence, promoting social engagement, facilitating personal contact, and providing access to resources (K. P. Smith & Christakis, 2008; Umberson & Karas Montez, 2010). Conversely, being socially isolated is associated with adverse outcomes such as depression, stress, and cognitive decline (Reiner & Steinhoff, 2024; Rohde et al., 2015; Shankar et al., 2011). Although social relationships are important for everyone, it is particularly important for older people who are at a stage in their lives when social contacts may change due to retirement, changes in income, loss of family and friends, disability, trouble getting around, hearing, vision, and memory loss etc. Studies focusing on older people shown that social contact impact their mental health (Reiner & Steinhoff, 2024), quality of life and cognitive functioning (Ayalon & Levkovich, 2018) and ultimately their possibilities of aging in place (Greenfield, 2016; Kemperman et al., 2019).

With regard to daily mobility in public and health literature, the focus is generally on the physical and cognitive limitations people may encounter to move and to carry out social activities. Other studies go further and consider people's activity spaces to account for both residential and non-residential areas that people are exposed to in their daily lives, adding a multi-geographic perspective to place-based effects on health outcomes (eg. Shareck et al., 2014; Vallée et al., 2011; Zhang et al., 2018). Again, the case of elderly group is particular, as daily mobility tends to decrease for people over 65 compared to other age groups: they make fewer daily trips, over shorter distances (Böcker et al., 2017; Hensher, 2007; Urbanek et al., 2023), their activity spaces are typically monocentric, with the home serving as the primary node and composed by familiar services in their immediate neighbourhood (Meijering et al., 2024).

Even if the geography of locations visited both with and without members of the social network could offer an effective approach to better understanding the social and geographical context of everyday life of elderly people, associations between the geographical location of daily activities and social networks remain understudied for the elderly, but also for all segments of the population (Reiner & Steinhoff, 2024). From a time geography perspective (Carrasco et al., 2008; Hägerstrand, 1970), understanding these patterns could help capture how temporal and spatial constraints shape social interactions and mobility in daily life. However, studies are limited to defining the social network geographies as the distribution in space of the social networks home location (Axhausen, 2005; Gramsch-Calvo & Axhausen, 2024a). They concentrated on the effects of spatial proximity of home locations of social network members (Andris, 2016; Andris & Sarkar, 2022; Becker et al., 2019; Carrasco et al., 2008; Litwin et al., 2015) on people mobility, overlooking the actual geographical places where interactions with social network members occur (Wang et al., 2015).

To explore in a combined way the social and geographical contexts of everyday life, and to fill some of the gaps in knowledge of the combination between social networks and daily mobility in elderly people, we propose here to explore what we call their "sociability space" – i.e. the geography of their social network interactions. By distinguishing locations visited with or without members of the social network, we aim to capture the sociability and non-sociability components of activity space. Such empirical research faces a number of methodological challenges, not least that of collecting comprehensive data about places of face-to-face interactions. A common method is to use questionnaires to ask people about their social interactions during their 'recreational' (also called 'discretionary' or 'hedonic') activities. Focusing solely on recreational activities risks overlooking that some interactions may also take place during 'utilitarian' (also called 'functional') activities. Another common method is to ask people only about the social interactions that take place in their neighbourhood of residence, without recording their exact location in that fuzzy spatial unit called 'neighbourhood', and without considering that some of these interactions may also take place outside the residential neighbourhood. However, social interactions in the neighbourhood of residence are only part of the picture: in the Paris metropolitan area, 41% of people report to meet their friends mainly outside their residential neighbourhood, and 38%

both in and outside their residential neighbourhood (Vallée et al., 2010). Finally, the most robust method with questionnaires is to combine a 'place generator' (asking respondents to list the places they visit according to a wide range of utilitarian and recreational activities) and a 'name generator' (asking respondents to list the people with whom they have social relations) (Naud et al., 2020). Combining these two generators is time-consuming for both respondents and interviewers, but gives a more complete picture of where and with whom people regularly interact (Chaix et al., 2012). This is the methodological approach we have chosen for the present research: we have used innovative map-based questionnaires (Chaix et al., 2012; Naud et al., 2020) which include both place and name generators and collect precise data about sociability (social interactions and social network structure) and activity space. Thanks to this data collection, we were able to draw distinction between the sociability and non-sociability components of activity space (the collection of activity places visited *with or without* members of social network) and to examine sociability differences in mobility behaviours on the basis of the full spectrum of daily activities, not just recreational activities (Gramsch-Calvo & Axhausen, 2024a, 2024b). Even if homes may serve as important spaces for social interaction (Anton & Lawrence, 2014), they are not considered as a sociability place in this study designed to capture social interactions occurring in out-of-home environments. Social interactions occurring in external environments, such as parks and cafés, provide insights into how urban contexts facilitate or constrain opportunities for sociability outside the domestic domain. By taking advantage of this methodological approach, we can address the three following objectives: (1) to explore the specificities of elderly people's *sociability* activity space in comparison to their *non-sociability* activity space by describing their structural characteristics (number of places, number of visits, diversity of the activities involved, average road network distance from home to the places, spatial extent and distance of home from the centre of the standard deviational ellipse); (2a) to observe whether the social network influences the structure of sociability and non-sociability activity space, and to (2b) determine if the sociability activity space is more strongly associated with the social network compared to the non-sociability activity space; (3) to evaluate the differences in how the sociability and non-sociability components of activity space are related to socio-demographic characteristics of elderly people and their residential profiles.

These three objectives are explored empirically among older people living in the Paris region (France). Like other major cities in the developed world, the population of the French capital is ageing. According to census data, people 60 and over account for 20% of the whole population in 2021 (16% in 2004). A third of residents aged 65 to 79 live alone and half of those aged 80 and over. The Paris region provides an interesting and illustrative setting for examining the relationship between daily mobility and social isolation, two facets of healthy ageing and ageing in place. Distinguishing between sociable and non-sociable activity spaces can greatly improve our understanding of how mobility patterns and social networks interact. This distinction makes it possible to identify areas and populations at risk of social isolation, reveal clusters of limited social interaction, and provide valuable insights for designing targeted urban policies and social interventions.

2 Data and methods

2.1 Survey

Data were collected in the Paris region (France) as part of the HANC (Healthy Aging and Networks in Cities) and MINDMAP (Promoting mental well-being and healthy aging in cities) projects. Participants were recruited from the RECORD cohort Study (Chaix et al., 2011).. Eestablished in 2007 for a total of 7290 participants RECORD cohort investigates the impact of environmental factors on health inequalities, focusing on urban and peri-urban areas of the Paris region. Each RECORD participant aged 60 and over was invited, via telephone and mail, to take part in the HANC and MINDMAP studies. Those who agreed to participate in these studies (n = 225) were subsequently contacted to complete a questionnaire covering sociodemographic information, personal social network members and on regular activities (Fernandes et al., 2020).

During the inclusion visit, participants' regular activity places and their social network were collected with a version of the VERITAS-Social questionnaire (Chaix et al., 2012; Naud et al., 2020), specifically built for these projects. VERITAS-Social is a map-based questionnaire that allows to geolocate regular activities done by the participant, to list each member of the social network (with no limits), to specify the relationships between network members (i.e., who know whom), and to declare whether places were visited alone or with a social network member. It integrates Google Maps' interactive mapping features, allowing users to search for, visualize, and geocode participants' activity locations. The computer-assisted questionnaire guides participants through a spatiotemporal cognitive journey, consisting of a series of screens with questions and interactive maps. This approach helps facilitate the reporting of spatial information (point data, polylines, polygons) while minimizing memory bias. The two components of the application – survey questions and interactive maps – work together to stimulate recall and provide more geographically accurate data compared to a simple questionnaire. Participants were first asked to list members of their social network. Subsequently, they were asked to list their regular activity places and to associate each of these activity places with one or more of member of their social network with whom they visit them. A regular activity is defined as an activity conducted at least once a month over the past 12 months. Participants were asked to identify locations where they met with members of their social network. In this step, the questionnaire allowed for the addition of social network members, as a participant might only remember a specific social network member when mentioning an activity place. For different categories of activities (whatever recreational or utilitarian), participants answer the question: “Usually, do you do this activity with other people?”. Furthermore, VERITAS-Social questionnaire links each social network member to the corresponding geographic place(s) by asking, “If you usually do this activity with other people, with whom?”. This methodological approach, which combines a "name generator" and a "place generator" (with a possible back-and-forth between the two generators), was chosen in order to collect as complete

data as possible on geographical locations of regular interactions with social network members. Lastly, participants were asked to identify “who knows whom” within their social relationships, providing the structural properties of their social networks.

Participants completed the survey in person (by telephone during the COVID-19 pandemic) from July 2019 to May 2021. During the first pandemic lockdown the survey was suspended and then restarted with the same study protocol but with additional health and hygiene practices to ensure minimal risk of contagion. After the first lockdown participants were asked to answer considering their habits before the lockdown.

2.2 Measures about sociability and non-sociability spaces

The geolocated activity places are grouped in 6 categories: grocery stores (e.g., supermarket, market, fishmonger); sport and recreational places (e.g., cultural or recreational activity, physical activity, restaurant); health places (e.g., doctor, pharmacy); workplaces; places for visits or accompaniment (accommodation, lodging or generic place of visit); other services (bank agency, post office, cemetery, hairdresser, ATM). Transport locations such as transit stations and bus stops were also collected but excluded for the present research. We then distinguish between sociability and non-sociability activity places according to whether the participants reported visiting them with a member of their social network or not, respectively. Activity places where locations outside the home in which face-to-face interaction occurs. Lastly, we exclude activity places located outside the Ile-de-France region in order to not generate bias in the geographical definition of the activity spaces (resulting in 5 sociable places out of 311 and 14 non-sociable places out of 965 being removed from the final dataset).

According to the literature on activity spaces (Perchoux et al., 2014; L. Smith et al., 2019), we describe sociability and non-sociability spaces with the following structural attributes (Table 1): number of places, number of visits (frequency of visits to places per month), diversity of places (number of categories as described above) and mean street network distance from residence to the locations in question. We also use the Directional Distribution tool in ArcGIS Pro to create two standard deviational ellipses (CI: 95%): one for sociable locations and another for non-sociable locations, based on visit frequency. We then calculate the area of these ellipses and measure the distance between the activity space's center of gravity and the residence. (Table 1).

Table 1: Description of structural attributes related to sociability and non-sociability spaces

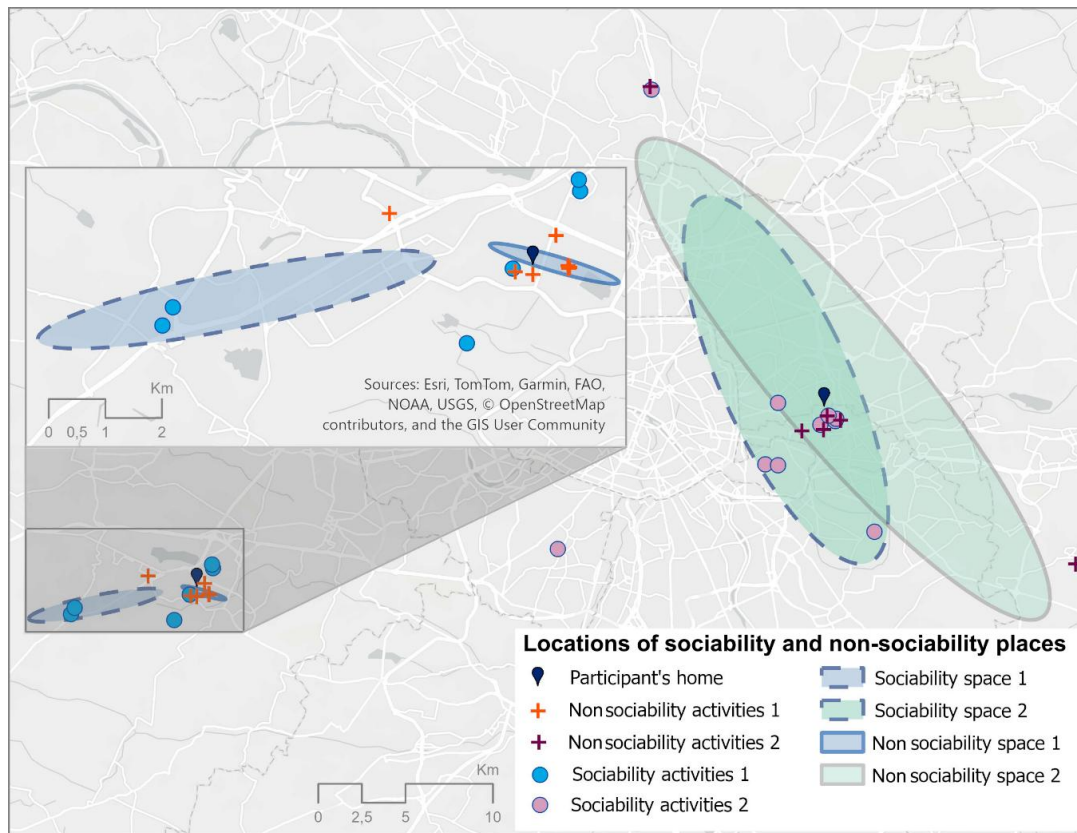
Name	Indicator	Range of values / Meaning	Reference
Number of places	Count of regular activity locations.	The number of places where ego usually performs social and non-social activities	(Lord et al., 2009)
Number of visits	Number of regular activity locations per respondent multiplied by the frequency of visits per month to each location.	The number of activities performed in a month	(Perchoux et al., 2014)
Diversity of places*	Evenness Index is calculated by first assessing the diversity of location across categories using the Shannon Index, then dividing it by its maximum possible value. 6 types of regular activity locations: Grocery stores; Other services; Sport and recreational places; Health places; Workplaces; Places for visits or accompaniment.	The diversity index is a mathematical measure of activity variety for each participant. It provides more information than the richness or the number of existing places uses, it also takes the relative abundances of different places types into account. It represents the extent to which each activity type is close in numbers for each participant. Indicating the richness of the different type of activity locations where ego usually performs social and non-social activities (varies between 0 and 1). 1 indicates a perfectly even distribution of categories (maximum diversity), 0 indicates that all activity is concentrated in a single category (no diversity).	(Perchoux et al., 2014; Shannon & Weaver, 1949)
Mean distance from residence to places	GIS processing. Mean street network distance (km) from the participant residence to the places.	The extent to which participants move in urban environment for activities, indicating the participants' behaviour to move across space to engage in social and non-social activities.	(Perchoux et al., 2014)
Spatial extent	GIS processing. Area (km ²) of standard deviational ellipse (95% CI) generated from the places (considering the frequency of visits)	The extent to which visited places are dispersed or concentrated in the urban space. A smaller area indicates that the places are more concentrated around the participant's residence. A larger area indicates that places are spread out over a wider area.	(Perchoux et al., 2014; Sherman et al., 2005)
Distance (km) between the center of gravity of the activity space and the residence	GIS processing. Euclidean distance (km ²) between the residence and the centroid of the standard deviational ellipse generated from the places (considering the frequency of visits).	It indicates how far individual residences are from the centre of the spatial distribution of all the places. A low eccentricity means that the distance between residences and the centroid is relatively consistent. High eccentricity suggests that the distance between residences and the centroid may vary significantly. It also indicates spatial distribution of activities (Lord et al., 2009)	(Lord et al., 2009; Perchoux et al., 2014; Sherman et al., 2005)

*For more details the reader is referred to the Supplementary materials

Figure 1 gives cartographic illustration for the locations of sociability and non-sociability places of two participants (and their respective standard deviational ellipses). Participant 1 is older than participant 2, has fewer social network connections (n=2) compared to participant 2, who has 6 alters in their networks. Participant 1 engages in fewer sociability activities (n=88) than participant 2 (n=100) but visits more non-sociability places (n=10) and participates in more non-sociability activities (n=117) than participants 2. Despite this, participant 1 travels, on average, 2 km less than participant 2 to perform activities and has smaller and less spatially dispersed sociability and non-sociability spaces.

All participants (n = 225) reported at least one non-sociability place while 14% reported no sociability place (Table 3). Diversity index and street network mean distance (requiring at least one place for the computation) were only calculated for the participants who reported at least one sociability place (n= 194). Attributes defined from standard deviational ellipses (area and distance between the center of gravity of the activity space and the residence (km)), requiring at least three places for the computation of the ellipse, were only computed for the respondents who reported to visit at least three sociability places (n = 115).

Figure 1: Locations of sociability and non-sociability places of two participants (and their respective standard deviational ellipses).



2.3 Measures about social network

The social network is a set of socially relevant nodes (network members) connected by one or more relations (Carrington, 2011; Newman, 2010). We have considered participants' social network as the ego-centred network of relationships that a person has with others. In this type of network, the participant is the central node (ego) and the alters are individuals with whom the ego has direct social ties or interactions. To investigate the associations between social network indicators and structural attributes of both sociability and non-sociability spaces, we use social network literature (Newman, 2010) to select six indicators: (1) the number of all contacts (email, phone call, face-to-face etc.) per week, (2) the number of face-to-face social interactions per week; (3) the number of social network members, i.e. the ego's degree; (4) the presence of a closed cohesive structure among the social network members, i.e. the global clustering coefficient; (5) similarity vs. diversity in alters according to types of relations (husband/wife, child, other household members, friends, co-workers, acquaintance), i.e. evenness index; (6) dispersion in alters' ages, i.e. variation coefficient for age. We provide a summary of these social network attributes in Table 2.

Table 2: Description of social network measures

Name	Indicator	Range of values / Meaning	Reference
Contacts (per week)	Number of all contacts (mail, phone call, face-to-face) per week.	Strength of in-person contacts.	(Fujiwara et al., 2022)
Face-to-face social interactions (per week)	Number of face-to-face social interactions per week.	Strength of in-person contacts.	(Fujiwara et al., 2022)
Degree	Number of connections from ego to alters.	The number of social network members with whom ego usually performs social activities.	(Newman, 2010)
Global Clustering*	The global clustering coefficient measures how often nodes in a network form triangles. It is the number of closed triplets (three nodes all connected to each other) divided by the total number of triplets (three nodes connected by at least two links). An open triplet has two links, while a closed triplet has three. Each triangle contains three closed triplets, one centered on each node.	The extent to which all social members are embedded in a closed cohesive structure (varies between 0 and 1; 0 indicating a sparse and disconnected structure and low cohesion; 1 indicating that nodes tend to form tightly interconnected groups or clusters, and are thus more cohesive).	(Newman, 2010)
Similarity of relationship types*	Evenness Index for types of relationship with alters, in 6 categories: husband/wife, child, other household members, friends, co-workers, acquaintance. It is calculated by dividing the Shannon diversity index by its maximum	The extent to which ego is connected with similar categories of people in his/her social network (varies between 0 and 1; 0 indicating dominance of one type of alter; 1 indicating the presence of all types of alters in equal numbers).	(Shannon & Weaver, 1949)
Variation coefficient in ages of alters*	The ratio of the standard deviation in alters' age (numeric) and the mean of alters' age (numeric) * 100	The extent to which social network members are of different ages. It is expressed as a percentage (0-100) and provides a standardized measure of the dispersion of the sample. A higher coefficient of variation indicates greater relative variability of alters' age, while a lower coefficient of variation suggests less variability relative to the mean.	(Bedeian & Mossholder, 2000)

*For more details the reader is referred to the Supplementary materials

2.4 Individual and residential characteristics

Individual profiles are defined from sociodemographic and economic factors: sex, age groups (2 categories: 60-70; >70), level of education (3 categories: low (less than *Baccalauréat*); middle (*bac et bac +2*); high (*bac + 3* and more)), household composition [2 categories: living alone or living not alone – i.e. with partner, children, relatives or friends), employment status (working or not working (i.e. unemployed, retired, housewife-man, other)]. Three groups of residential locations are defined: Paris municipality (2.2 million inhabitants; 18% of population of the whole Paris region), large municipalities (44 municipalities between 50,000 and 200,000 inhabitants; 24% of the population of the whole region) and small municipalities (1223 municipalities with less than 50,000 inhabitants; 58% of the population of the whole region) (Vallée et al., 2015).

2.5 Statistical methods

Descriptive statistics were computed for sociodemographic and residential variables, for social network indicators and the corresponding sociability and non-sociability places metrics. We use chi-square tests to compare distributions of the sociability and non-sociability places according to the 6 types of places (grocery stores; sport and recreational places; health places; workplaces; places for visits or accompaniment; other services). Since the vast majority of measures concerning sociability and non-sociability spaces and social networks are not normally distributed, we compare their median values from non-parametric Wilcoxon tests and use violin plots and boxplots to depict data distribution. We estimate their correlation from Spearman's rank correlation. Wilcoxon test allows to compare median differences between groups, while Spearman's rank correlation allows to focus on whether the variables increase or decrease together in a consistent direction. When comparing median values of structural attributes of sociability spaces according to individual profiles and to residential location, we use Wilcoxon tests for variables with two groups and Kruskal-Wallis tests for variables with more than two groups. Kruskal-Wallis tests compare median differences in distribution of values between two groups. As a comparison, we make the same for structural attributes of non-sociability spaces. In order to consider the pre and post Covid survey period, we also made a robustness check of data collected (Wilcoxon test) (see Annex 3).

3 Results

3.1 Sample description

We used data collected among a sample of 225 people aged 60 years and older and living in the Paris Region (Île-de-France). As shown in Table 3, participants were more often males (64%), not living alone (67%), and with high education level (55%, in line with the Grand Paris population statistics with 49.8 % having bac+2 and over in 2021 (INSEE, 2024)). There were roughly similar proportions of individuals aged 60-70 (56%) and over 70 (54%), with most of them being retired (85%). Residential locations were well distributed within the metropolitan area (30% in Paris city centre, 39% in medium suburbs and 31% in small suburbs), with most respondents (65%) being interviewed after the first Covid-19 pandemic lockdown.

Table 3: Descriptive statistics of the sample of respondents (n=225)

Sex, n (%)	
Women	81 (36%)
Men	144 (64%)
Age, n (%)	
60-70 years	126 (56%)
>70 years	99 (44%)
Household composition, n (%)	
Living not alone	151 (67%)
Living alone	74 (33%)
Education level, n (%)	
Low (less than Baccalauréat)	43 (19%)
Middle (Baccalauréat and Baccalauréat +2)	59 (26%)
High (Baccalauréat + 3 and more)	123 (55%)
Employment status, n (%)	
Not retired (working, unemployed, others)	34 (15%)
Retired	191 (85%)
Residential location, n (%)	
Paris centre	68 (30%)
Medium suburbs	87 (39%)
Small suburbs	70 (31%)
Period of data collection, n (%)	
Pre first Covid lockdown (July 22, 2019 - March 12, 2020)	79 (35%)
Post first Covid lockdown (March 17, 2020 - May 28, 2021)	146 (65%)
Number of sociability places, n (%)	
None	31 (14%)
One or two	79 (35%)
Three or more	115 (51%)
Social network measure, median (interquartile range - IQR)*	
Number of contacts per week	94.5 (83.25)
Number of face-to-face contacts per week	59.5 (52.5)
Degree	6 (4)
Global Clustering	0.83 (0.53)
Evenness of relationship types	0.39 (0.25)
Variation coefficient in ages of alters	31.1 (22.0)

* n=214

3.2 Differences between sociability and non-sociability spaces

All 225 participants reported engaging in daily activities in a total of 3351 places (Table 4). Among these places, grocery stores emerged as the most frequently visited, accounting for 35% of the visits, followed by "other services" (25%) and sport and recreational places (22%). Of all visits to activity locations, 77% were done alone and 23% with members of their social network. These proportions greatly vary according to the types of activity locations: grocery stores, other services and health services are predominantly visited alone (83%, 98% and 97% respectively) and sport and recreational places are predominantly visited with members of the social network (62%). See Table 4 for the detailed distributions of sociability and non-sociability places.

Table 4: Distribution of the sociability and non-sociability places types for all participants (n=225)

	Total	Sociability places (i.e., visited with social network members)	Non-sociability places (i.e., visited without social network member)	Chi2 test (X^2 , p-value), df=1
	Number (%)			
Grocery stores	1161 (35%)	201 (17%)	960 (83%)	479.19, <0.0001
Other Services	851 (25%)	16 (2%)	835 (98%)	802.48, <0.0001
Sport and recreational places	753 (22%)	467 (62%)	286 (38%)	46.38, <0.0001
Health services	405 (12%)	12 (3%)	393 (97%)	360.42, <0.0001
Work places	37 (1%)	15 (40%)	22 (59%)	1.32, 0.25
Places for visits or accompaniment	144 (4%)	60 (42%)	84 (58%)	25.59, 0.045
Total	3351 (100%)	771 (23%)	2580 (77%)	1003, <0.0001

After aggregating data at the respondent level, we observed that there are fewer activity places and visits per month when focusing on participants' sociability places (median values of 3 and 34 respectively; p-value < 0.0001) rather than on their non-sociability places (median values of 11 and 174 respectively; p-value < 0.0001). Sociability places were more homogeneous than non-sociability places, with median diversity index values of 0.30 and 0.69 (p-value < 0.0001), respectively. This is also evident in the violin plots in Figure 2, where non-sociability places show greater diversity, with values concentrated in the higher-density range of the distribution. In contrast, sociability spaces exhibit a more uniform distribution across the diversity index. Sociability places are further away from the residence than non-sociability places (Median values of 2.74 *versus* 1.69 km; p-value < 0.0001). Areas of sociability spaces (as measured from the standard deviational ellipse) are larger than areas of non-sociability spaces (median values of 4.12 km² *versus* 2.69 km², respectively; p-value = 0.008). Both violin plots, for sociability and non-sociability areas, display long tails, indicating occasional extreme values in the area distributions. Additionally, sociability spaces are more decentered from residences compared to non-sociability spaces (median values of distance between the center of gravity of the activity space and the residence of 1.15 km *versus* 0.68 km; p-value < 0.0001). This is also reflected by the two violin plots of the distance indicators: values for non-sociability spaces are more concentrated in the lower distance range, while those for sociability spaces are more evenly distributed across the entire distance spectrum. See Table 5 for a detailed comparison between sociability and non-sociability spaces and Figure 2 for the distribution of structural variables.

Figure 2: Distribution of Sociability and Non Sociability spaces structural attributes from violin plots and boxplots

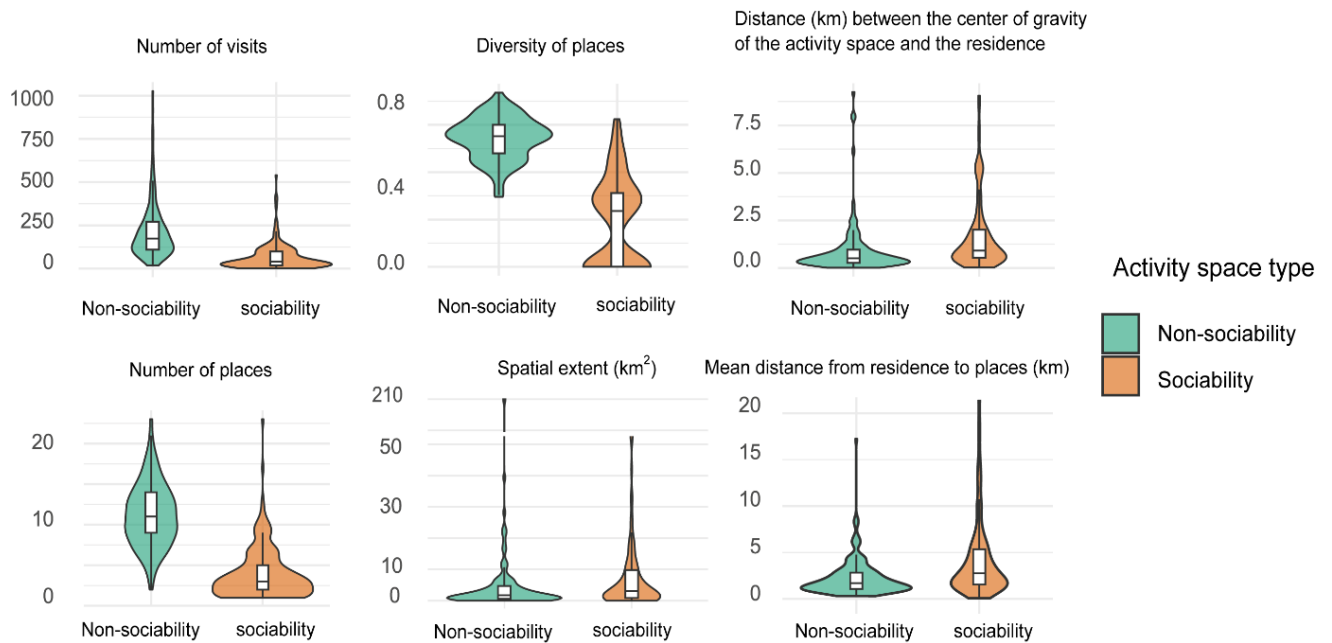


Table 5: Comparison between structural attributes of sociability space and non-sociability space: differences in median values and correlation coefficients

	Number of places (n=225)	Number of visits per month (n=225)	Diversity of places (n=194)	Mean distance from residence - in km (n=194)	Area (ellipse) - in km ² (n=115)	Distance between the center of gravity and the residence (ellipse) - in km (n=115)
	Median (IQR)					
Sociability space	3 (4)	34 (76)	0.30 (0.39)	4.12 (3.8)	3.01 (9.01)	1.15 (1.48)
Non-Sociability space	11 (5)	174 (163)	0.69 (0.15)	2.69 (1.77)	1.69 (4.15)	0.68 (0.69)
<i>Wilcoxon-test V (p-value)</i>	575.5 (<0.0001)	1715.5 (<0.0001)	233 (<0.0001)	14198 (<0.0001)	4285 (0.008)	4995 (<0.0001)
	Correlation between sociability and non-sociability space					
Correlation coefficient	-0.15	-0.1	-0.11	0.22	0.18	0.1
<i>Spearman rank test CI (p-value)</i>	-0.27, -0.02 (0.03)	-0.23, 0.03 (0.14)	-0.24, 0.04 (0.14)	0.08, 0.35 (0.00)	0.00, 0.35 (0.05)	-0.08, 0.28 (0.28)

The six structural attributes of sociability and non-sociability spaces appear to be weakly correlated with each other (see Table 5). Correlations are close to zero for the number of visits (ρ : -0.1), diversity of places (ρ : -0.11) and distance between the center of gravity of the activity space and the residence (ρ : 0.13). A weak negative correlation is found for the number of places (ρ : -0.15) which means that the more sociability places there are, the fewer non-sociability places there are. Two weak and positive correlations appear for the mean distance from residence and for the standard deviational ellipse area (ρ : 0.22 and ρ : 0.2) which means that the greater the distance to sociability places, the greater the

distance to non-sociability places. However, all the correlations are weak (none of them exceeds |0.22|), which indicates relative independence between measures of sociability space and non-sociability space.

3.3 Correlations of social networks indicators with sociability and non-sociability spaces

Social network indicators were available for 214 participants. The median number of all contacts per week was 94.5 and decreased to 59.5 when considering only face-to-face contacts. Participants had a median of 6 alters. Their social networks were in median highly cohesive, as indicated by the clustering coefficient. There is generally a low diversity of relationship types with alters and a small variation in their age (See Table 3 for social networks description). In Table 6 we see that the structural characteristics of sociability space were more closely linked to social network measures compared to non-sociability space. Ten significant correlations ($p < 0.05$) with social network measures were found for indicators related to sociability space, and only two for indicators related to non-sociability space.

Table 6: Correlation between social network measures and structural attributes of sociability and non-sociability space (spearman tests).

	N. of contacts	N. of face-to-face contacts	Degree	Global Clustering	Similarity of relationship types	Variation coefficient in ages of alters
Number of places (n=214)						
Sociability space	0.15*	0.36****	0.19**	0.03	0.01	0.14*
Non-sociability space	0.07	-0.09	0.19**	-0.11	0.08	0.02
Number of visits per month (n=214)						
Sociability space	0.03	0.2**	0.13*	0	0	0.02
Non-sociability space	0.1	0.04	0.01	0.1	0	0.13*
Diversity of places (n=185)						
Sociability space	0.29****	0.43****	0.03	0.2**	0.01	0.23**
Non-sociability space	0.11	0.03	-0.04	-0.06	0.01	0.09
Mean distance from residence (n=185)						
Sociability space	0.07	-0.07	0.06	-0.07	0.08	0.05
Non-sociability space	0.04	0.02	0.01	0.01	0.1	0.05
Area (n=112)						
Sociability space	0.15	0.17*	0.15	-0.06	-0.11	0.13*
Non-sociability space	0.06	0.01	0.12	-0.08	0.25**	-0.11
Distance between the center of gravity and the residence (n=112)						
Sociability space	0.11	0.05	0.09	-0.07	0.08	0.09
Non-sociability space	0.12	0.1	0.09	0.02	0.00	0.06

*' p<0,1; '** p<0.05; ***' p<0.01; ****' p<0.001

More precisely we observed the following correlations values in Table 6: the number of places visited with social network members is positively correlated with the number of contacts ($\rho: 0.15$) - with a stronger association when we consider only number of face-to-face contacts ($\rho: 0.36$), the degree of the

network (ρ : 0.19), and the variation of age of the members of the social network (ρ : 0.14). The number of visits per month in sociability places is positively associated with the number of face-to-face contacts (ρ : 0.2) and with the degree of the network (ρ : 0.13). Positive correlations are also found between the diversity of sociability places and (i) the total number of social contacts, with a stronger association with face-to-face contacts (ρ : 0.43), (ii) the global clustering (ρ : 0.2) (indicating cohesion among members of the social network) and (iii) variation in age among alters (ρ : 0.23). Also, the area of the sociability space is positively correlated with the number of face-to-face contacts (ρ : 0.17). The correlations between structural dimensions of sociability space and social network features have a maximum value of 0.43. We consider correlations in the range of approximately 0.3–0.5 to be meaningful, as human behavior is influenced by multiple factors, making very high correlations uncommon.

3.4 Individual and residential factors related to sociability and non-sociability spaces

Table 7 provides a summary of the variability in structural attributes of sociability and non-sociability spaces based on participants' socioeconomic profiles and residential locations. Of the 72 associations considered, there are slightly more statistically significant associations ($p < 0.05$) with individual and residential characteristics for sociability space indicators than for non-sociability space indicators (13 and 11 respectively). Moreover, it is rare for one socio-demographic indicator to be similarly associated to one attribute of sociability space and non-sociability space.

Regarding gender, we find differences according to regular daily sociability locations: the median number of non-sociability places is higher for women than for men (median values respectively of 13 and 10; p -value = 0.0016). Men move to a more diverse range of sociability places than women (respectively 0.33 *versus* 0; p -value = 0.007). The violin plot for men (see Figure 3 in Annex 4), appears more elongated and narrower, indicating a wider range of values but lower density in any single interval. In contrast, the plot for women is shorter, with variable width (sometimes broader, sometimes very narrow) suggesting a more concentrated distribution with potential peaks or clustering at specific values. Younger respondents and those not retired visited a more diverse range of sociability places compared to elderly and retired ones. Additionally, younger respondents visit sociability and non-sociability places further away from their residence, more dispersed and more decentered from their residence compared to older respondents. Working people travel further from home than retired people, whether for sociability activities or not.

Participants living alone tend to have a greater number of non-sociability places, and a smaller number of sociability places (median values of 13 non-sociability places and 2 sociability places) when compared to individuals living in a multi-person household (median values of 10 non-sociability places and 3 sociability places; p -value = 0.0003). Compared to individuals living in a multi-person household, their sociability places are also less diverse and less spatially extended (1.52 *versus* 3.27 km²; p -value = 0.05).

The number of sociability places, their frequency of visit (i.e., number of visits per month) as well as their spatial dispersion are found to increase with education level, while no trends appear for non-sociability places.

Regarding residential location, the non-sociability places of inhabitants of Paris center are more numerous, are visited more frequently, gather a wider range of activities and are closer to the place of residence than the sociability places of the inhabitants of medium and small suburbs. This reflects the higher spatial concentration of essential services and urban density in Paris center. Interestingly, when focusing on sociability places, a notable trend emerges: half of residents of small suburbs travel over 3.6 km to reach sociability destinations, compared to 2.4 km for Paris center residents and just 1.9 km for those in medium suburbs (p-value = 0.0019). In contrast, for non-sociability places, the average median distance traveled by residents of small and medium suburbs remains close to 1.9 km, while for those in central Paris it is only around 1.3 km, highlighting a greater density and accessibility of basic services in the central Paris (p-value = 0.03).

Table 7: Variation in structural attributes of sociability space and non-sociability space according to individual and residential characteristics: differences in median values

	Number of places (n=225)		Number of visits per month (n=225)		Diversity of places (n=194)		Mean distance from residence - in km (n=194)		Area (ellipse) - in km ² (n=115)		Distance between the center of gravity of the activity space and the residence - in km (n=115)	
	Sociability space	Non sociability space	Sociability space	Non sociability space	Sociability space	Non sociability space	Sociability space	Non sociability space	Sociability space	Non sociability space	Sociability space	Non sociability space
Sex												
Female	2	13	34	168	0	0.68	2.27	1.83	2.54	3.22	0.71	0.64
Male	3	10	33.5	176	0.33	0.69	3.16	1.58	3.02	1.51	1.11	0.44
<i>Wilcoxon-test: V</i>	5630	7306	5885	5598	3388	4454	3867	4654	1428	1720	1254	1652
<i>(p-value)</i>	(0.66)	(0.0016)	(0.90)	(0.61)	(0.007)	(0.76)	(0.20)	(0.40)	(0.83)	(0.12)	(0.21)	(0.26)
Age												
60-70	3	11	31.5	178	0.31	0.7	3.21	1.94	4.59	2.43	1.31	0.63
>70	3	11	36	163	0	0.68	2.08	1.39	1.55	1.21	0.72	0.40
<i>Wilcoxon-test: V</i>	6485	6642	6317	6349	5390	5016	5582	6007	2098	2100	2037	2037
<i>(p-value)</i>	(0.60)	(0.40)	(0.87)	(0.81)	(0.03)	(0.28)	(0.011)	(0.0003)	(0.008)	(0.008)	(0.02)	(0.02)
Household composition												
Living not alone	3	10	36	172	0.32	0.69	2.63	1.79	3.27	1.51	0.91	0.57
Living alone	2	13	32	184	0	0.68	2.76	1.47	1.52	2.72	1.29	0.34
<i>Wilcoxon-test V</i>	7222	4156	6100	5398	5556	3866	3857	4189	1510	1095	1179	1564
<i>(p-value)</i>	(0.0003)	(0.0018)	(0.26)	(0.68)	(<0.001)	(0.67)	(0.65)	(0.64)	(0.05)	(0.42)	(0.80)	(0.02)
Employment status												
Not retired	3	10.5	56	183	0.365	0.68	4.28	2.11	5.42	2.33	1.94	0.7
Retired	3	11	32	170	0.25	0.69	2.43	1.58	2.51	1.48	0.88	0.44
<i>Wilcoxon-test V</i>	3258	3152	3835	3555	3076	2372	3103	2968	937	950	1111	1122
<i>(p-value)</i>	(0.97)	(0.78)	(0.37)	(0.37)	(0.02)	(0.75)	(0.02)	(0.07)	(0.41)	(0.35)	(0.02)	(0.02)
Education level												
Low	2	12	24	174	0.31	0.69	2.91	2.08	1.63	1.69	1.17	0.36
Middle	3	12	36	161	0.14	0.68	2.13	1.56	2.06	1.27	0.78	0.46
High	3	11	36	178	0.31	0.69	3.28	1.59	5.54	1.91	0.96	0.60
<i>Kruskal-test χ^2</i>	5.24	1.31	4.81	0.74	0.03	0.41	2.33	0.54	5.34	0.42	1.37	4.03
<i>(p-value)</i>	(0.07)	(0.51)	(0.09)	(0.69)	(0.98)	(0.81)	(0.31)	(0.76)	(0.06)	(0.81)	(0.50)	(0.13)
Residential location												
Paris centre	3	13	36	205	0.2	0.72	2.43	1.30	2.02	1.57	1.07	0.38
Medium Suburbs	3	11	26	161	0.31	0.68	1.92	1.93	2.07	1.94	0.83	0.631
Small suburbs	3	10	38	156	0.34	0.67	3.64	1.88	5.54	1.46	1.40	0.464
<i>Kruskal-test χ^2</i>	0.58	9.79	1.16	6.11	2.80	7.26	12.51	6.76	5.01	1.38	4.03	3.99
<i>(p-value)</i>	(0.74)	(0.007)	(0.56)	(0.047)	(0.24)	(0.02)	(0.0019)	(0.03)	(0.08)	(0.50)	(0.13)	(0.13)

4 Discussion

This study explores the way in which interactions with social network members are embedded in people's activity space and examines the relevance of distinguishing a 'sociability space' from a 'non-sociability space' among elderly inhabitants of the Paris region.

With regard to the type of activities, we showed that two thirds (62%) of places traditionally associated with 'recreational' activities (e.g. sport and recreational places) and about a fifth (18%) of places traditionally associated with 'utilitarian' activities (e.g. grocery shops) are visited with social network member(s). These findings highlight that face-to-face interactions with social network members should not be assumed to occur exclusively or necessarily in places or during activities categorized as 'recreational'. All everyday activities - whatever their purpose - may shape social context and promote social interactions with members of their social network. This finding is particularly relevant to remember for older people: they rely on social contacts for aging in place (Greenfield, 2016; Kemperman et al., 2019) and their mental health is positively associated with social network structure, regardless of whether the activities undertaken with social network members are utilitarian or recreational (Umberson & Karas Montez, 2010).

By comparing activity places visited with social network members ("sociability places") to those visited alone ("non-sociability places"), we observed significant differences in their structural characteristics: sociability places exhibit lower diversity, higher spatial dispersion and greater distance from residence compared to non-sociability places. Moreover, the structural characteristics of sociability and non-sociability spaces appear to be weakly correlated. If the correlation had been strong, we might have concluded that there was no point in describing these two spaces separately, since they would have been somewhat redundant. However, this is not the case. These weak correlations highlight the importance of splitting activity places into sociability and non-sociability places and considering their respective geographies as they provide different information. It is in the light of these weak correlations that the following results on the relationships of sociability spaces (and non-sociability spaces) with social networks measures and respondent profiles should be interpreted.

Regarding social network measures, we observe stronger and more numerous correlations with the structural characteristics of sociability space than with the structural characteristics of the non-sociability space. This is a second element that confirms the value of splitting the activity space into sociability and non-sociability spaces in order to consider the geographical components of interactions with social network members. Especially, a larger number of social network members, along with greater network cohesion and stronger social ties, was positively related to the number of places visited, the diversity of these visits, and the geographic extent of the sociability space. These results align with previous research (Gramsch-Calvo & Axhausen, 2024a; Rosso et al., 2013), underlining that social interactions directly affect venue variety, while the quality of the social network influences awareness of neighbourhood

activities, promoting their growth in number. Also, high mobility supports community integration while limited mobility may accelerate isolation among older adults (Pantelaki et al., 2020). This stresses the importance to the size of the network and its cohesion to avoid social isolation.

The last main finding concerns the different patterns in the way sociability and non-sociability spaces are related to the socio-demographic and residential profiles of the respondents. The results suggesting that the characteristics of egos, their personal networks and residential profiles influence the spatial distribution of relationships and can help us understand where people engage in social activities with others. Dividing activity space into sociability and non-sociability spaces made it possible to reveal, for example, trends according to gender or household composition, and above all, to highlight how mobility and sociability differ significantly for more vulnerable populations such as older women living alone and with lower levels of education. Compared to men, women tend to visit more non-sociability places but have less diverse sociability places. These findings may be related to gender inequalities in mobility devoted to domestic tasks such as shopping. This domestic activity reproduces and positions women within traditional discourses of housewife and mother, restricting and reducing their access to well-defined leisure time with members of their social networks (Cockburn-Wooten et al., 2008). Such gender differences resonate with literature on gender inequalities in time use among working-age households, but also among older people (Adjei et al., 2017).

People living alone tend to visit more non-sociability places but less sociability places compared to those in multi-person households. Such findings show that social isolation at home may be cumulative with a risk of social isolation outside the home, aligning with previous research findings and emphasizing the health risks (as depression, stress, and cognitive decline) faced by older people living alone (Reiner & Steinhoff, 2024; Rohde et al., 2015; Shankar et al., 2011).

In line with previous research on public health (Che Had et al., 2023) our results also indicate that as age increases, mobility decreases, particularly for activities conducted alone. It highlights the travel difficulties that older people are more likely to face as they age, especially if they are unable to rely on the help of a member of their social network.

Interesting trends also appear with education level and are observed exclusively for sociability places. For instance, higher education levels correlate with a greater number of sociability places, more frequent visits, and a wider dispersion of these locations. This trend adds another element to our understanding of the mechanisms that drive the social gradient in health: according to their level of education, older people cannot count on the same sociability space for healthy ageing and ageing in place.

The number of sociability places and the frequency of visits do not differ according to residential location but their geography does: sociability places of people living in central Paris and in medium-sized suburbs are spatially less dispersed and closer to their residences than sociability places of people living in the small suburbs. This may be because inhabitants of denser areas enjoy a higher density of services and a more multifunctional environment which favors meetings with social network members

in the vicinity of their homes, particularly for people with mobility limitations (Allam et al., 2024; Thaury et al., 2024), or temporal constraints (Carrasco et al., 2008; Hägerstrand, 1970). This geographical pattern of sociability places according to residential location contributes to enriching the specific literature on the role of geographical contexts in the structure of social networks (Cayouette-Remblière & Charmes, 2024; Favre et al., 2022) as well as the more general literature on the repercussions of motility, social capital (Cuignet et al., 2019; Kaufmann et al., 2004) and urban design (Jacobs, 1961; Talen, 1999) on social relations.

All these empirical findings highlight the importance of incorporating sociability interactions into activity spaces in scientific studies, but also in public policies. They underline the interest for policy makers to consider promote sociability and mobility among the elderly as a synergistic strategy yielding to mutual benefits: increased socialization encourages mobility, while increased mobility facilitates access to social opportunities and to maintain social contacts. As an example, we can cite public policies that promote the creation of sociability spaces by identifying public spaces that facilitate social interaction, and the design of accessible urban environments that encourage spontaneous social encounters, such as plazas, cafes, and walking paths. Public policies promoting the development of age-friendly communities could help reduce social isolation among older adults and support community-based initiatives that organize social activities and events. It may also be beneficial to consider how even non-leisure spaces like doctors' offices, pharmacies, and supermarkets could be equipped with accessible public areas to foster social interactions during daily functional activities. Finally, our findings point to the potential value of extending 15-minute city strategies beyond central urban areas to suburban contexts. Enhancing proximity between residential locations, essential services, and socialization spaces in suburban areas could help reduce inequalities in access to social opportunities, especially for more vulnerable populations.

Regarding limitations, the present research is based on a small sample of respondents, smaller than samples issued from social media and mobile phones (Andris & Sarkar, 2022). Some recent studies use digital data (such as mobile data) to locate social interactions and visualise geospatial flows, such as Facebook friendships, among very large samples of digital users. Despite the enthusiasm for such big data, it should be recognised that it often lacks personal socio-demographic information for confidentiality reasons, and is often not very precise geographically contrary to what one might expect (Vallée & Lenormand, 2023). They also do not provide information about interpersonal relationships (Andris, 2016) and neglect certain segments of the population, such as older people, who are less likely to use social media (Andris & Sarkar, 2022).

Here, we do not include the ego's home as a sociability space, even if we recognize the relevance of the home in certain social dynamics (Anton & Lawrence, 2014; Easthope, 2004). We made the choice to focus on public or semi-public environments that may promote spatial practices of sociability beyond

the private domain. Including the home would have introduced a fundamentally different type of social space, characterized by intimacy and restricted access, which is not directly comparable to shared and accessible out-of-home places.

Because of our small sample, we choose to only measure bivariate (and not multivariate) associations, and not to check for interactions. In addition, we are careful not to interpret statistical associations in terms of causality. Since our results are specific to the context of the Paris region, we are also aware that they are not generalizable to other environments, whether rural or in regions with different cultural, social and economic contexts. Additionally, the comparatively high education level in the sample may reflect a volunteer bias, which limits the generalizability of the findings and may result in sociability–space measures being biased upward.

Data collection took place before and after Covid-19 period. Respondents that answered after Covid-19 period had to answer their pre-Covid-19 mobility patterns which may lead to some memory bias. Actually no significant change was observed in the majority of the outcomes (see Annex 3). Only the mean distance from residence and the area of the ellipse for non-sociability space were found to be larger when data collection occurred after Covid-19 period.

Another set of limitations comes from bias related to data collection since we rely on self-reported mobility and regular activity behaviors, which could imprecisely reflect the actual spatial behavior of participants. Future studies using objective measures (such as GPS tracking) or ecological momentary assessment should complement these empirical results, even if this means recruiting a more limited sample of respondents. Moreover, sociability spaces may vary according to the strength of social ties, as individuals are often willing to travel greater distances to meet with close contacts. Future studies should consider incorporating tie strength into spatial structures of sociability spaces. Furthermore, our focus on social interactions with network members may overlook the importance of more casual social interactions with people who are not sufficiently known to be recorded as members of a social network. Future research should explore the role of these less structured forms of social interaction. In summary, our recommendations for future studies would be to (1) analyze how members of the whole social network (ego and alters) move and interact in geographical space; (2) to consider the duration of social interactions, as some of them may be ephemeral, while others may be stronger due to the longer period over which people exchange (Andris & Sarkar, 2022).

5 Conclusion

The spatial patterns of social interactions are a fundamental aspect of social activity and mobility behavior, yet research on how these interactions influence movement and activity locations is still very limited. In this paper we introduced the new concept of “sociability places” to add a social dimension to the traditionally socially blind notion of activity space. We showed that the characteristics of

sociability places and non-sociability places largely differ and are not similarly associated with traditional a-spatial measures of social networks. Additionally, we emphasised that sociability spaces vary according to individual and residential profiles in a different way than non-sociability spaces. From a time-geography perspective, these patterns can be understood in terms of space–time paths influenced by constraints, highlighting how temporal and spatial factors shape opportunities for social engagement. By displaying a precise picture of how people interact with their social network members in the geographical area, this empirical work provides new information on the mobility and social interaction of older people. It also provides a methodological demonstration that combining social networks and mobility patterns can help identify populations and areas at risk of social isolation, such as elderly people living alone and those with low levels of education, offering guidance for the design of urban and social policies. Also, by using geographical indicators coupled with network ones, it gives empirical insights into spatial patterns of social interactions that are more refined than those in prior studies relying only on topological or aggregate measures. Furthermore, we highlight the relevance of distinguishing between sociability and non-sociability activity spaces, not only to understand the mobility patterns of older adults, but also to strengthen the broader case for studying sociability across diverse population groups and urban contexts. They could also be used by policymakers to develop policies aimed at both promoting everyday mobility and reducing social isolation.

6 Bibliography

- Adjei, N. K., Brand, T., & Zeeb, H. (2017). Gender inequality in self-reported health among the elderly in contemporary welfare countries: A cross-country analysis of time use activities, socioeconomic positions and family characteristics. *PloS One*, *12*(9). <https://doi.org/10.1371/JOURNAL.PONE.0184676>
- Allam, Z., Amir, R., Lassaube, U., Chabaud, D., Moreno, C., Allam, Z., Amir, R., Lassaube, U., Chabaud, D., Moreno, C., Allam, Z., Khavarian-garmsir, A. R., Lassaube, U., Chabaud, D., & Moreno, C. (2024). *Mapping the Implementation Practices of the 15-Minute City To cite this version : HAL Id : hal-04666669 smart cities Mapping the Implementation Practices of the 15-Minute City*.
- Andris, C. (2016). Integrating social network data into GISystems. *International Journal of Geographical Information Science*, *30*(10), 2009–2031. <https://doi.org/10.1080/13658816.2016.1153103>
- Andris, C., Liu, X., & Ferreira, J. (2018). Challenges for social flows. *Computers, Environment and Urban Systems*, *70*(April), 197–207. <https://doi.org/10.1016/j.compenvurbsys.2018.03.008>
- Andris, C., & Sarkar, D. (2022). Handbook of Spatial Analysis in the Social Sciences. In S. J. Rey & R. Franklin (Eds.), *Handbook of Spatial Analysis in the Social Sciences*. Edward Elgar Publishing. <https://doi.org/10.4337/9781789903942>
- Anton, C. E., & Lawrence, C. (2014). Home is where the heart is: The effect of place of residence on place attachment and community participation. *Journal of Environmental Psychology*, *40*, 451–461. <https://doi.org/10.1016/J.JENVP.2014.10.007>
- Axhausen, K. W. (2005). Activity spaces, biographies, social networks and their welfare gains and externalities: Some hypotheses and empirical results. *Arbeitsbericht Verkehrs- Und*

- Ayalon, L., & Levkovich, I. (2018). A Systematic Review of Research on Social Networks of Older Adults. *Gerontologist*, 59(3), E164–E176. <https://doi.org/10.1093/GERONT/GNX218>
- Becker, C., Kirchmaier, I., & Trautmann, S. T. (2019). Marriage, parenthood and social network: Subjective well-being and mental health in old age. *PLoS ONE*, 14(7), 1–20. <https://doi.org/10.1371/journal.pone.0218704>
- Berkman, L. F., & Kawachi, I. (2000). A Historical Framework for Social Epidemiology. *Social Epidemiology*, 1–16. <https://doi.org/10.1093/med/9780195377903.003.0001>
- Berkman, L. F., Kawachi, I., & Glymour, M. M. (Eds.). (2014). *Social Epidemiology* (Second Edi). Oxford University Press. <https://doi.org/10.1093/med/9780195377903.001.0001>
- Böcker, L., van Amen, P., & Helbich, M. (2017). Elderly travel frequencies and transport mode choices in Greater Rotterdam, the Netherlands. *Transportation*, 44(4), 831–852. <https://doi.org/10.1007/S11116-016-9680-Z/FIGURES/3>
- Carrasco, J. A., Miller, E. J., & Wellman, B. (2008). How far and with whom do people socialize?: Empirical evidence about distance between social network members. *Transportation Research Record*, 2076, 114–122. <https://doi.org/10.3141/2076-13>
- Carrington, P. J. . S. J. (2011). *The SAGE Handbook of Social Network Analysis*. 1–640.
- Cayouette-Remblière, J., & Charmes, E. (2024). Social ties in and out of the neighbourhood: Between compensation and cumulation. *Urban Studies*, 61(8), 1581–1603. <https://doi.org/10.1177/00420980231212298>
- Chaix, B., Kestens, Y., Bean, K., Leal, C., Karusisi, N., Meghrief, K., Burban, J., Fon Sing, M., Perchoux, C., Thomas, F., Merlo, J., & Pannier, B. (2011). Cohort profile: Residential and non-residential environments, individual activity spaces and cardiovascular risk factors and diseases—The RECORD cohort study. *International Journal of Epidemiology*, 41(5), 1283–1292. <https://doi.org/10.1093/ije/dyr107>
- Chaix, B., Kestens, Y., Perchoux, C., Karusisi, N., Merlo, J., & Labadi, K. (2012). An interactive mapping tool to assess individual mobility patterns in neighborhood studies. *American Journal of Preventive Medicine*, 43(4), 440–450. <https://doi.org/10.1016/j.amepre.2012.06.026>
- Che Had, N. H., Alavi, K., Md Akhir, N., Muhammad Nur, I. R., Shuhaimi, M. S. Z., & Foong, H. F. (2023). A Scoping Review of the Factor Associated with Older Adults’ Mobility Barriers. *International Journal of Environmental Research and Public Health*, 20(5), 4243. <https://doi.org/10.3390/IJERPH20054243>
- Chen, Z., Kelty, S., Evsukoff, A. G., Welles, B. F., Bagrow, J., Menezes, R., & Ghoshal, G. (2022). Contrasting social and non-social sources of predictability in human mobility. *Nature Communications* 2022 13:1, 13(1), 1–9. <https://doi.org/10.1038/s41467-022-29592-y>
- Cockburn-Wootten, C., Pritchard, A., Morgan, N., & Jones, E. (2008). “It’s her shopping list!” Exploring gender, leisure, and power in grocery shopping. *Leisure/Loisir*, 32(2), 407–436. <https://doi.org/10.1080/14927713.2008.9651416>
- Cuignet, T., Perchoux, C., Caruso, G., Klein, O., Klein, S., Chaix, B., Kestens, Y., & Gerber, P. (2019). Mobility among older adults: Deconstructing the effects of motility and movement on wellbeing. *Urban Studies*, 57(2), 383–401. <https://doi.org/10.1177/0042098019852033>
- Easthope, H. (2004). A place called home. *Housing, Theory and Society*, 21(3), 128–138. <https://doi.org/10.1080/14036090410021360>
- Favre, G., Figeac, J., Grossetti, M., & Tudoux, B. (2022). Social distance in France: Evolution of homogeneity within personal networks from 2001 to 2017. *Social Networks*, 68, 70–83. <https://doi.org/10.1016/J.SOCNET.2021.05.001>
- Fernandes, A., Van Lenthe, F. J., Vallée, J., Sueur, C., & Chaix, B. (2020). Linking physical and social environments with mental health in old age: A multisensor approach for continuous real-life ecological and emotional assessment. *Journal of Epidemiology and Community Health*. <https://doi.org/10.1136/jech-2020-214274>

- Golledge, R. G., & Stimson, R. J. (1997). Spatial behaviour: a geographic perspective. In *Spatial behaviour: a geographic perspective*. <https://doi.org/10.2307/144350>
- Gramsch-Calvo, B., & Axhausen, K. W. (2024a). Exploring the influence of social relations and knowledge of the urban environment on leisure travel. *Journal of Transport Geography*, *117*(September 2023). <https://doi.org/10.1016/j.jtrangeo.2024.103860>
- Gramsch-Calvo, B., & Axhausen, K. W. (2024b). The importance of the social environment on leisure destination choice: A mixed multinomial analysis of homophilic preferences. *Environment and Planning B: Urban Analytics and City Science*, *0*(0), 1–19. <https://doi.org/10.1177/23998083241303198>
- Greenfield, E. A. (2016). Support from Neighbors and Aging in Place: Can NORC Programs Make a Difference? *The Gerontologist*, *56*(4), 651–659. <https://doi.org/10.1093/GERONT/GNU162>
- Hägerstrand, T. (1970). What about people in regional science? *Papers in Regional Science*, *24*(1), 7–24.
- Hasanzadeh, K., Laatikainen, T., & Kyttä, M. (2018). A place-based model of local activity spaces: individual place exposure and characteristics. *Journal of Geographical Systems*, *20*(3), 227–252. <https://doi.org/10.1007/s10109-017-0264-z>
- Hensher, D. A. (2007). Some Insights into the Key Influences on Trip-Chaining Activity and Public Transport Use of Seniors and the Elderly. *International Journal of Sustainable Transportation*, *1*(1), 53–68. <https://doi.org/10.1080/15568310601097004>
- INSEE. (2024). *Education and training in 2021: inter-communality metropolis du Grand Paris*. https://www.insee.fr/en/statistiques/6457611?geo=EPCI-200054781#tableau-FOR_G2
- Jacobs, J. (1961). *The Death and Life of Great American Cities* (1st ed.). Random House, New York.
- Kaufmann, V., Bergman, M. M., & Joye, D. (2004). Motility: mobility as capital. *International Journal of Urban and Regional Research*, *28*(4), 745–756. <https://doi.org/10.1111/J.0309-1317.2004.00549.X>
- Kemperman, A., Van Den Berg, P., Weijs-Perrée, M., & Uijtdewillegen, K. (2019). Loneliness of older adults: Social network and the living environment. *International Journal of Environmental Research and Public Health*, *16*(3). <https://doi.org/10.3390/ijerph16030406>
- Kestens, Y., Wasfi, R., Naud, A., & Chaix, B. (2017). “Contextualizing Context”: Reconciling Environmental Exposures, Social Networks, and Location Preferences in Health Research. *Current Environmental Health Reports*, *4*(1), 51–60. <https://doi.org/10.1007/s40572-017-0121-8>
- Lee, J. Y., & Kwan, M. P. (2011). Visualisation of socio-spatial isolation based on human activity patterns and social networks in space-time. *Tijdschrift Voor Economische En Sociale Geografie*, *102*(4), 468–485. <https://doi.org/10.1111/j.1467-9663.2010.00649.x>
- Litwin, H., Stoeckel, K. J., & Schwartz, E. (2015). Social networks and mental health among older Europeans: are there age effects? *European Journal of Ageing*, *12*(4), 299–309. <https://doi.org/10.1007/s10433-015-0347-y>
- Lord, S., Joerin, F., & Thériault, M. (2009). La mobilité quotidienne de banlieusards vieillissants et âgés: Déplacements, aspirations et significations de la mobilité. *Canadian Geographer*, *53*(3), 357–375. <https://doi.org/10.1111/j.1541-0064.2009.00269.x>
- Meijering, L., Osborne, T., van Doorne, M., & Weitkamp, G. (2024). Seasonal differences in mobility and activity space in later life: a case study of older adults in the Northern Netherlands. *Mobilities*, *19*(4), 736–755. <https://doi.org/10.1080/17450101.2023.2289453>
- Naud, A., Sueur, C., Chaix, B., & Kestens, Y. (2020). Combining social network and activity space data for health research: tools and methods. *Health and Place*, *66*(September). <https://doi.org/10.1016/j.healthplace.2020.102454>
- Newman, M. (2010). *Networks: An Introduction*. Oxford University Press. <https://doi.org/10.1093/acprof:oso/9780199206650.001.0001>
- Pantelaki, E., Maggi, E., & Crotti, D. (2020). Mobility impact and well-being in later life: A multidisciplinary systematic review. *Research in Transportation Economics*, *86*, 100975.

<https://doi.org/10.1016/J.RETREC.2020.100975>

- Perchoux, C., Kestens, Y., Thomas, F., Hulst, A. Van, Thierry, B., & Chaix, B. (2014). Assessing patterns of spatial behavior in health studies: Their socio-demographic determinants and associations with transportation modes (the RECORD Cohort Study). *Social Science and Medicine*, *119*, 64–73. <https://doi.org/10.1016/j.socscimed.2014.07.026>
- Perkins, J. M., Subramanian, S. V., & Christakis, N. A. (2015). Social networks and health: A systematic review of sociocentric network studies in low- and middle-income countries. *Social Science & Medicine*, *125*(10), 60–78. <https://doi.org/10.1016/j.socscimed.2014.08.019>
- Puura, A., Silm, S., & Masso, A. (2022). Identifying relationships between personal social networks and spatial mobility: A study using smartphone tracing and related surveys. *Social Networks*, *68*, 306–317. <https://doi.org/10.1016/J.SOCNET.2021.08.008>
- Reiner, A., & Steinhoff, P. (2024). The association of social networks and depression in community-dwelling older adults: a systematic review. *Systematic Reviews*, *13*(1), 1–23. <https://doi.org/10.1186/s13643-024-02581-6>
- Rohde, N., D'Ambrosio, C., Tang, K. K., & Rao, P. (2015). Estimating the Mental Health Effects of Social Isolation. *Applied Research in Quality of Life* *2015 11:3*, *11*(3), 853–869. <https://doi.org/10.1007/S11482-015-9401-3>
- Rosso, A. L., Taylor, J. A., Tabb, L. P., & Michael, Y. L. (2013). Mobility, disability, and social engagement in older adults. *Journal of Aging and Health*, *25*(4), 617–637. <https://doi.org/10.1177/0898264313482489>
- Shankar, A., McMunn, A., Banks, J., & Steptoe, A. (2011). Loneliness, Social Isolation, and Behavioral and Biological Health Indicators in Older Adults. *Health Psychology*, *30*(4), 377–385. <https://doi.org/10.1037/A0022826>
- Shareck, M., Frohlich, K. L., & Kestens, Y. (2014). Considering daily mobility for a more comprehensive understanding of contextual effects on social inequalities in health: A conceptual proposal. *Health & Place*, *29*, 154–160. <https://doi.org/10.1016/j.healthplace.2014.07.007>
- Smith, K. P., & Christakis, N. A. (2008). Social Networks and Health. *Annual Review of Sociology*, *34*(1), 405–429. <https://doi.org/10.1146/annurev.soc.34.040507.134601>
- Smith, L., Foley, L., & Panter, J. (2019). Activity spaces in studies of the environment and physical activity: A review and synthesis of implications for causality. *Health and Place*, *58*(April). <https://doi.org/10.1016/j.healthplace.2019.04.003>
- Talen, E. (1999). Sense of Community and Neighbourhood Form: An Assessment of the Social Doctrine of New Urbanism. *Urban Studies*, *36*(8), 1361–1379. <https://doi.org/10.1080/0042098993033>
- Thaury, M. O., Genet, S., Maurice, L., Tubaro, P., & Berkemer, S. J. (2024). City composition and accessibility statistics in and around Paris. *Frontiers in Big Data*, *7*, 1354007. <https://doi.org/10.3389/FDATA.2024.1354007/BIBTEX>
- Umberson, D., & Karas Montez, J. (2010). Social Relationships and Health: A Flashpoint for Health Policy. *Journal of Health and Social Behavior*, *51*(1_suppl), S54–S66. <https://doi.org/10.1177/0022146510383501>
- Urbanek, A., Acedański, J., & Krawczyk, G. (2023). Depopulation or ageing? Decomposing the aggregate effects of projected demographic changes on urban transport systems. *Journal of Transport Geography*, *111*, 103662. <https://doi.org/10.1016/J.JTRANGE0.2023.103662>
- Vallée, J., Cadot, E., Grillo, F., Parizot, I., & Chauvin, P. (2010). The combined effects of activity space and neighbourhood of residence on participation in preventive health-care activities: The case of cervical screening in the Paris metropolitan area (France). *Health & Place*, *16*(5), 838–852. <https://doi.org/10.1016/J.HEALTHPLACE.2010.04.009>
- Vallée, J., Cadot, E., Roustit, C., Parizot, I., & Chauvin, P. (2011). The role of daily mobility in mental health inequalities: The interactive influence of activity space and neighbourhood of residence on depression. *Social Science and Medicine*, *73*(8), 1133–1144. <https://doi.org/10.1016/j.socscimed.2011.08.009>

- Vallée, J., Le Roux, G., Chaix, B., Kestens, Y., & Chauvin, P. (2015). The ‘constant size neighbourhood trap’ in accessibility and health studies. *Urban Studies*, *52*(2), 338–357. <https://doi.org/10.1177/0042098014528393>
- Vallée, J., & Lenormand, M. (2023). Intersectional approach of everyday geography. <https://doi.org/10.1177/23998083231174025>, *51*(2), 347–365. <https://doi.org/10.1177/23998083231174025>
- Wang, Y., Kang, C., Bettencourt, L. M. A., Liu, Y., & Andris, C. (2015). Linked Activity Spaces: Embedding Social Networks in Urban Space. In *Computational Approaches for Urban Environments* (pp. 313–336). Springer International Publishing. https://doi.org/10.1007/978-3-319-11469-9_13
- Ye, X., & Liu, X. (Eds.). (2019). *Cities as Spatial and Social Networks*. Springer International Publishing. <https://doi.org/10.1007/978-3-319-95351-9>
- Zhang, C. J. P., Barnett, A., Sit, C. H. P., Lai, P. C., Johnston, J. M., Lee, R. S. Y., & Cerin, E. (2018). Cross-sectional associations of objectively assessed neighbourhood attributes with depressive symptoms in older adults of an ultra-dense urban environment: The Hong Kong ALECS study. *BMJ Open*, *8*(3), 1–13. <https://doi.org/10.1136/bmjopen-2017-020480>
- Zhao, M., Liang, W., Xu, G., & Li, Z. (2019). Cities as spatial and social networks. In *Human Dynamics in Smart Cities*. <https://doi.org/10.1007/978-3-319-95351-9>

Supplementary material

1 Respondents without sociability activity space

Table A1: Descriptive statistics of the sample of respondents without sociability activity space(n=31)

Sex, n (%)	
Women	11 (34%)
Men	20 (66%)
Age, n (%)	
60-70 years	13 (42%)
>70 years	18 (58%)
Household composition, n (%)	
Living not alone	18 (57%)
Living alone	13 (43%)
Education level, n (%)	
Low (less than Baccalauréat)	13 (40%)
Middle (Baccalauréat and Baccalauréat +2)	9 (30%)
High (Baccalauréat + 3 and more)	9 (30%)
Employment status, n (%)	
Not retired (working, unemployed, others)	4 (3%)
Retired	27 (87%)

2 Measures

2.1 Diversity of places (sociability and non-sociability)

- 1- Measure the proportion of 6 types of regular activity locations: Grocery stores; Other services; Sport and recreational places; Health places; Workplaces; Places for visits or accompaniment
- 2- Calculate the evenness index (0-1, with 1 max equity) as:

$$Diversity\ of\ places = - \sum_k (p_k \ln p_k) / \ln N$$

where k is the category of activity location; p is the proportion of the locations within a specific activity category; N is the number of activity categories types.

The diversity index is a mathematical measure of activity variety for each participant. It provides more information than the richness or the number of existing places uses, it also takes the relative abundances of different places types into account. It represents the extent to which each activity type is close in numbers for each participant. Indicating the richness of the different type of activity locations where ego usually performs social and non-social activities (varies between 0 and 1). 1 indicates a perfectly even distribution of categories (maximum equity), 0 indicates that all activity is concentrated in a single category (no equity).

2.2 Global clustering

The global clustering coefficient is the number of closed triplets (or 3 x triangles) over the total number of triplets (both open and closed). A triplet is three nodes that are connected by either two (open triplet) or three (closed triplet) undirected ties. A triangle consists of three closed triplets, one centred on each of the nodes.

$$\text{Global Clustering} = \frac{\text{Number of closed triplets}}{\text{Total number of triplets}}$$

2.3 Similarity of relationship type

- 1- Measure the proportion of 6 types of relationship with alters: husband/wife, child, other household members, friends, co-workers, acquaintance
- 2- Calculate the evenness index (0-1, with 1 max equity) as:

$$\text{Similarity of relationship type} = - \sum_k (p_k \ln p_k) / \ln N$$

where k is the type of relationship; p is the proportion of the alters within a specific type of relationship; N is the number of type of relationship.

The extent to which ego is connected with similar categories of people in his/her social network (varies between 0 and 1; 0 indicating dominance of one type of alter; 1 indicating the presence of all types of alters in equal numbers).

2.4 Variation coefficient in ages of alters

$$\text{Variation coefficient in ages of alters} = \frac{\text{standard deviation in alters' age}}{\text{mean of alters' age}} \times 100$$

It represents the extent to which social network members are of different ages. It is expressed as a percentage (0-100) and provides a standardized measure of the dispersion of the sample. A higher coefficient of variation indicates greater relative variability of alters' age, while a lower coefficient of variation suggests less variability relative to the mean.