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Urban fabric and social participation in community-based elderly care facilities

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ABSTRACT

Apart from providing essential care for elderly inhabitants, a well addressed purpose of community-based elderly care facilities is to promote social integration through encouraging visitors from the neighbourhood to continuously participate in activities and use services offered by the facility. The location of care facilities and their local environment have been widely argued to constitute a critical factor for older people's continuous participation, which induces the formation and maintenance of personal networks between the different user groups, as well as a sense of attachment. However, existing literature on care facility location and older people's participation predominantly uses qualitative methods, and often applied to a single case. This causes ambiguity and controversy when comparing findings from different cases and also makes the generalisation of study findings problematic. This paper introduces a spatial network model which based on Space Syntax theory to explicitly describe spatial relations between care facilities and urban fabric. With a large dataset of social participation records from 91 community-based elderly care facilities in the Chinese city of Nanjing, the study will investigate how differentiated locational properties exert influence on patterns of older people's social participation. Findings indicate that local-scale spatial properties could influence occurrence patterns of social participation in care facilities, and the mechanism local-scale spatial properties exert influence varies in differentiated global-scale spatial contexts.

KEYWORDS

Community-based elderly care facility, social participation, spatial networks

1 INTRODUCTION

Since population ageing has been regarded as a challenge to human society in the 20th century, a range of concepts or models regarding elderly care have been proposed by either researchers or policy makers (Beyer and Nierstrasz, 1967, Mens and Wagenaar, 2010). With emerging research findings in the second half of the last century, addressing older people's loneliness and isolation

in traditional care institutions and their negative impact on physical, cognitive health and care expenditure (Bitzan and Kruzich, 1990, Takahashi et al., 1997, Bassuk et al., 1999), concepts such as ‘deinstitutionalisation’, ‘community-based care’ and ‘ageing in place’ became widely accepted in the world and nowadays is regarded as a vital aspect in achieving ‘successful ageing’. To transform from ‘medical’ to ‘social’ model of care, physical environments of care facilities, including both locational and architectural aspects, play a structural role in meeting elderly people’s social demand (Van Steenwinkel et al., 2017). One of the most significant spatial transformation is that large-scale care institutions located in the outskirts are gradually replaced by small- or medium-scale care facilities located in urban communities, with the underlying notion that social integration can be achieved through spatial integration (De Syllas, 1999).

Nowadays many kinds of care facilities rooted in urban communities with the aim of providing social support for the ageing population have been built all around the world, such as senior centres, community day care centres, multiple purpose residential care facilities and etc. Older people’s social participation in these facilities is well documented in academic research. However, their spatial relationships with urban fabric remain to be clarified. Few studies have introduced advanced and fine-grained spatial analysis methods into the study of care facilities. Their location and spatial distribution are usually broadly described with qualitative terms, which results in controversial findings regarding socio-spatial relationships. From a Space Syntax perspective, ‘located-in-communities’ does not necessarily mean ‘connected-well-with-communities’. Spatial relations between care facilities and their surrounding urban fabric at multiple scales can be structural factors shaping the way local residents access care facilities. This paper will introduce a spatial network model based on Space Syntax theory to explicitly describe spatial relations between care facilities and urban fabric. With a large number of social participation data from 91 community-based elderly care facilities in the Chinese city of Nanjing, the study will investigate how differentiated locational properties exert influence on patterns of older people’s social participation.

2 LITERATURE REVIEW

In the realm of elderly care studies, different terminologies are used in different countries to describe care facilities offering services for local communities (Wright, 1995), such as senior centres in Australia and Northern America, resource centres in the UK and the Netherlands, social care centres and day care centres in other contexts. In Chinese context, those care facilities serving mainly for local people are named as community-based elderly care facilities (CECF). These facilities usually have very few long-term care beds, focusing mainly on providing catering, social, health and day-care services for local people. A representative and widely adopted model similar to CECF in China is senior centres in Northern America. It is reported that there are over 11400 senior centres in the United States in 2017, most of which offer services such as nutrition, health and fitness, recreation, volunteer opportunities and social services (Pardasani and Thompson, 2010, Kadowaki and Mahmood, 2018). Although studies

found that meal programmes formed the core service for the majority of senior centres (Krout, 1997), surveys on older residents showed that social interaction and companionship are the major motivation of participation. A survey involving 856 participants from 27 senior centres conducted by Turner (2004) showed that 87% of respondents regarded social interaction with others as the primal reason for participating in meal programmes offered by senior centres, and 64% relied solely on senior centre in their life to socialise with others. Previous studies on participants of senior centres suggested that these people are more likely to be female, older and living alone (Kadowaki and Mahmood, 2018). Ashida and Heaney (2008) found those with higher intention of participation are more likely to have fewer social network members living in close proximity and lower levels of social connectedness. This strengthens the role of social activities as the core of services in senior centres.

Benefits of actively attending senior centres and participating in social activities are far reaching and have been extensively discussed. Researchers argued that senior centres can provide stimulating social environment for the elderly people to establish social support systems in their later life (Hutchinson and Gallant, 2016). Members of senior centres felt less isolated and experienced a greater level of social support than their non-participating counterparts. Some studies found attending activities in senior centres can promote psychological well-being, and reduce levels of stress and depression (Pardasani and Thompson, 2010). In general, all those benefits can help prevent premature institutionalisation of the elderly people, by slowing down the process of physical and cognitive decline (Aday et al., 2018).

Some research explored factors which may facilitate or impede older people's participation in senior centres, such as organisation models, programming, policy issues and physical environments. Hickerson and colleagues (2008) proposed that organisational resources, personal capital and relation capital are three main factors which conduce to active participation. Walker et al. (2004) found having activity groups with proper size, knowing about activities, involving in faith-based activities and having access to available transportation are factors relating to higher levels of participation. However, as stated by Kadowaki and Mahmood (2018) in a scoping review of senior centre in Canada and the United States, studies focusing on physical environment of senior centres and its influence are rather rare, especially those paying attention to the location of senior centres.

Community-based elderly care facilities, especially schemes like senior centres, which accept considerable number of users from local communities, will more or less be influenced by urban environments, with regard to the scope of visitors, frequency of participation, public awareness and etc. Quite a few previous studies on care facilities have pointed out that location is a pivotal factor in promoting community integration and participation. For instance, Reed et al. (1998) found that older residents can generate a sense of 'knowing' about a facility through passing by it on routes of their everyday life, thus being more inclined to use or reside in the future. Corden

and Wright (1993) argued that closeness to local amenities such as town centres or council offices is an important reason for elderly people to choose a facility, because at these locations they are easier to meet other people and participate in social activities. Cheng et al. (2012) proposed that information access or community presence of residential care resources, which to certain extent supported by location (geographical access) is an important aspect influencing older people's decision-making process. As for senior centres, Rosenberg (2015) pointed out that the lack of awareness in the wider community is one factor resulting in the shrinkage of members in senior centres in Australia. By investigating community-based care facilities in a Chinese city, Wang et al. (2017) found that isolated location could restrict the actual usage and public awareness.

Although relationships between location and older people's participation in care facilities have been discussed by previous researchers, it is worth noting that few studies have developed explicitly defined quantitative metrics to describe 'location'. Qualitative descriptions such as 'close to' or 'proximity to' are commonly used to define spatial relations between care facilities and urban environments. These concepts may vary significantly in different contexts and make it problematic to generalise research findings, e.g., how close is 'close'. On the other hand, most metrics employed in existing studies on older people's social participation in care facilities treat 'people' as basic entities and describe various aspects of people, such as their socio-demographic attributes, perception of loneliness and frequency of participation. Few studies treat a large number of facilities as basic entities to study their long-term performance in terms of older people's social participation.

3 DATA AND METHODS

3.1 Study area, context and data

This study is conducted in the Chinese city of Nanjing, the capital city of Jiangsu Province in Eastern China, which is one of the most economically developed, but also 'oldest' region in the country (Jiangsu Provincial Government, 2018). In this context, Nanjing was selected as a pilot city by Chinese government in 2014 to explore approaches of establishing comprehensive elderly care systems. The municipal government planned to provide care facilities for elderly people in all urban communities in the following five years. The study area in this paper contains two districts in the main city of Nanjing—Jianye and Qinhuai Districts. Both districts incorporate urban settings of the inner city, outer city and newly developed areas (Figure 1). A total number of 91 elderly care facilities are included.

The data of older people's social participation in care facilities used in this paper came from a big-data system called 'Smart Elderly Care' launched by the municipal government of Nanjing in October 2019. Each older resident (over 60 years old) who intends to use care services will receive an 'elderly service card' issued by his/her local community centre. With the card, a

resident can purchase or use services in local community care facilities. The card-swiping data, which records older people's usage time and types of activities, is collected by the system, with the aim of assisting both local governments and facility management teams to evaluate and optimise service provision, thus making elderly care services more efficiency and 'smarter'.



Figure 1: Study area and location of all care facilities

The dataset of 'social participation' recorded by the system, which is used in this paper, contains 41275 records in 91 facilities in total, including 31 types of social activities, such as birthday parties, singing and dancing clubs, tea parties, Taiji clubs, calligraphy clubs, card and chess, crafting, movie watching and etc. It is worth noting that this paper focuses merely on the overall participation pattern of social activities in care facilities, i.e., the total number of participations in different time period, rather than diving into specify types of social activities and exploring their characteristics in different facilities. Therefore, social activities are broadly defined in this study, following the original classification of the data-collection system, as a range of activities with main purposes of social interaction and entertainment, apart from other major types of activities such as catering, assisted bathing, therapy, health examination and skill training, though these activities may also be regarded as 'social' to certain degree.

Due to the outbreak of Covid in early 2020 and the strict lockdown policy in China, most care facilities in Nanjing were closed during late January and late April. Hence, only the data from May 1st to December 31st in 2020 is used in this study. The data was authorised to the author by Departments of Elderly Care Services from governments of Jianye and Qinhuai Districts for the purpose of academic research. The data was anonymised by the governments so that no personal information is included. The research project has received ethical approval from UCL's Research Ethics Committee (ID:17187/001).

3.2 Spatial network model and facility classification

To comprehensively describe the spatial relation between care facilities and their surrounding urban communities, a spatial network model composed by facilities and urban street segments is proposed in this study. In the model, street segments (divided by intersections) are regarded as nodes. Edges between two nodes are defined as two segments sharing the same intersection. This segment model is widely used in Space Syntax studies and other urban spatial network research (Marshall et al., 2018, Turner, 2007). Various network properties can be calculated based on this model. In this study, to further incorporate care facilities into the model, we connect facilities with segments on which their entrances are located and assign spatial properties of the segments to corresponding care facilities. In this way the spatial relation between care facilities and urban environments can be quantitatively described and evaluated (Li and Sailer, 2021).

Three types of metrics are used in this study as spatial variables to describe network properties of care facilities, which are Integration (closeness centrality), Choice (betweenness centrality) and Density (degree centrality). Integration and Choice in this paper are calculated following the algorithm developed by Hillier et al. (2012), i.e., normalised syntactic metrics based on angular distance. Density (degree centrality) is computed as the totally number of segments (nodes) weighted by their length within certain radius from a given facility, also known as Metric Reach as proposed by Peponis et al. (2008). All three types of metrics are calculated at multiple radii from local to global scales, including 250, 500, 750, 1000, 2500, 5000 meters and ∞ . Density at ∞ is eliminated from calculation because every facility will have the same density value if all segments of the model are taken into account. It should be pointed out that the spatial network model is constructed at the whole city level (see Figure 1), much larger than the study area, which is a common approach used in spatial network studies aiming at avoiding the ‘edge effect’ (Gil, 2015). Integration and Choice values are calculated in the DepthmapX platform, and Density values are calculated in the ArcGIS platform.

After model construction and variable computation, K-means clustering algorithm will be employed to classify care facilities according to their spatial properties. Since all three types of spatial metrics (integration, choice and density) are calculated at multiple scales (from R250 to ∞), a total number of 20 syntactic variables will be generated in this study. Considering that certain degree of correlation may exist between these metrics, and large number of input variables will violate the accuracy of K-means algorithm and increase the difficulty of interpretation of clustering results, Principal Component Analysis (PCA) will be used to extract key variables (factors) from the original 20 syntactic variables. Only those extracted variables will be used as inputs of K-means algorithm to classify care facilities. As another common procedure before running K-means, the optimal number of clusters (i.e., the K value) should be determined. In this study, a widely adopted metrics, the sum of squared distance within cluster (distortion) will be calculated and a knee-point detection algorithm will be used to pick a validate cluster number (Brun et al., 2007, Satopaa et al., 2011).

3.3 Social variables

In this paper, to characterise the pattern of social participation in care facilities, three social variables are proposed, the *long-term consistency* (LT_Con), *short-term consistency* (ST_Con) and *average capacity* (Ave_Cap). During the period of investigation (eight months from May to December 2020), we define ‘*active days*’ (AD) as the total number of days in one month when social activities are recorded in a facility. Accordingly, ‘*active month*’ (AM) is defined as a month when active days (AD) in that month is larger than zero, i.e., social activities occur in that month.

Long-term consistency (LT_Con) of social participation in a facility is defined as the total number of active months for that facility from May to December 2020 (8 months). It describes the extent to which social activities occur consistently in a care facility in the long term. LT_Con is calculated as the equation below, where AD_i is the number of active days in the i^{th} month.

$$LT_Con = \sum_{i=1}^8 AM_i \quad (\text{if } AD_i > 0, AM_i = 1; \text{ otherwise, } AM_i = 0)$$

Short-term consistency (ST_Con) of social participation in a facility is the average number of active days in all active months for that facility. ST_Con is a complementary metric of LT_Con in that it describes the average participation rate of a facility in the short term (one month). ST_Con is computed as the equation below.

$$ST_Con = \frac{\sum_{i=1}^8 AD_i}{LT_Con}$$

Average capacity (Ave_Cap) of social participation of a facility is the average daily number of records of social activities in that facility in all active days during the study time. It describes the average capacity of a facility in absorbing social participation in one day. The calculation of Ave_Cap can be represented as the equation below, where M is the total times of participations throughout the study time.

$$Ave_Cap = \frac{M}{\sum_{i=1}^8 AD_i}$$

3.4 Testing socio-spatial relation

Considering that care facilities will be classified into several clusters by their spatial properties, to explore socio-spatial relations, One-way ANOVA test will be employed in this paper. The test compares differences of mean values among multiple groups of elements and examines whether those differences are statistically significant. A post hoc comparison, with LSD method (Least Significant Difference), is also conducted to perform pairwise comparisons between group means, which demonstrates explicitly the difference of social variables between each pair of spatial clusters.

4 RESULTS AND FINDINGS

4.1 Classification of care facilities

The formerly defined three groups of spatial variables (NAIN, NACH, DENS) are calculated at multiple scales based on the spatial network model. Values of spatial variables are then assigned to care facilities from their connected street segments. The correlation matrix in Figure 2 demonstrates that within each group, syntactic metrics at adjacent scales highly correlate with each other, especially those metrics at global scales. As discussed in section 3.2, Principal Component Analysis will be performed to extract fewer numbers of key variables from the original ones, which benefits further clustering analysis.

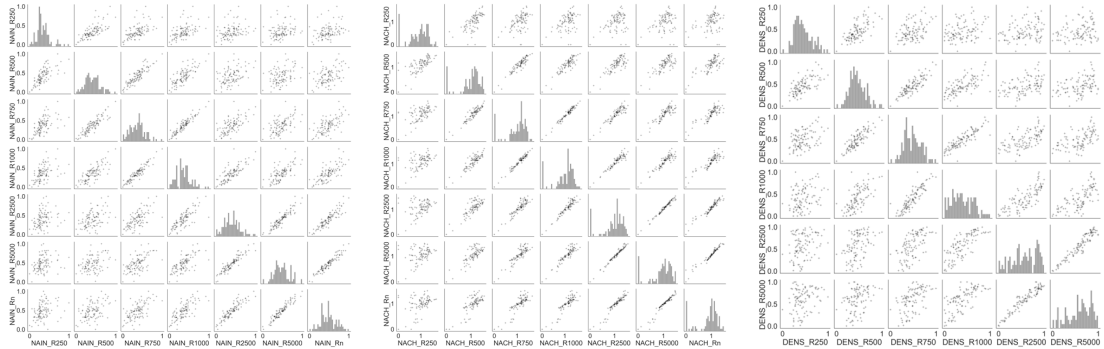


Figure 2: Correlation matrix of syntactic metrics at multiple scales

Table 1 shows the result of Principal Component Analysis on each group of original syntactic metrics. Within each group, two key factors are extracted. For all three groups, the values of Total Variance Explained are over 85 percent, indicating that the extracted factors can sufficiently represent the variance of original metrics. As indicated by the loadings (contribution of original metrics) of extracted factors, they feature either global-scale metrics or local-scale metrics in their groups. Thus, according to values of factor loadings, the six extracted factors are named as NAIN_Glo, NAIN_Loc, NACH_Glo, NACH_Loc, DENS_Glo and DENS_Loc.

Table 1: Results and factor loadings of Principal Component Analysis on original syntactic metrics

Original variables	Extracted variables		Original Variables	Extracted variables		Original Variables	Extracted variables	
	NAIN_Glo	NAIN_Loc		NACH_Glo	NACH_Loc		DENS_Glo	DENS_Loc
NAIN_Rn	.937	.236	NACH_Rn	.917	.352	-----	-----	-----
NAIN_R5000	.961	.156	NACH_R5000	.920	.373	DENS_R5000	.940	.098
NAIN_R2500	.937	.247	NACH_R2500	.921	.381	DENS_R2500	.949	.175
NAIN_R1000	.666	.664	NACH_R1000	.869	.477	DENS_R1000	.807	.455
NAIN_R750	.519	.794	NACH_R750	.833	.533	DENS_R750	.600	.695
NAIN_R500	.244	.931	NACH_R500	.746	.638	DENS_R500	.324	.902
NAIN_R250	.050	.856	NACH_R250	.356	.927	DENS_R250	.032	.854
Total Variance Explained	89.550%		Total Variance Explained	97.903%		Total Variance Explained	86.279%	

Based on the extracted spatial variables, K-means clustering algorithm is performed to classify care facilities into different groups. In this study, clustering is conducted sequentially in two phases, the global-scale and the local-scale clustering. Firstly, at global scale, global density (DENS_Glo) is used to classify all 91 facilities. Secondly, within each group of facilities classified in the first phase, local variables, 'NAIN_Loc', 'NACH_Loc' and 'DENS_Loc' are employed to conduct a local-scale clustering. The reason of classifying facilities at two phases lies in the social and spatial nature of care facilities. On the one hand, participants of social activities in care facilities are mainly older residents living in local areas, usually within a 500-meter catchment area (about 10-minute walk), which is also a planned 'service area' for community-based care facilities in Nanjing. Therefore, older people's movement behaviours related to social participation in care facilities are largely localised movements, which may be influenced by local-scale spatial properties. On the other hand, global location of care facilities in the city, e.g., in inner city or outer city, is also a vital contextual factor (Schorr et al., 2017, Levasseur et al., 2015). Among big cities in the world, ageing population is more aggregated in inner city areas whereby they have more choices of venues for social activities. In Nanjing, residential areas in the inner city are usually small but well-connected communities, whereas in the outer city, people live in large, gated communities. These varied spatial contexts may result in different patterns of facility usage for older people.

As shown in Figure 3, in the first phase, K-means algorithm generates three clusters based on global density values of care facilities. The result can largely represent the distance between facilities and the centre of the city. The first cluster is facilities in the inner city, where density of street network is the highest. The second cluster is facilities in the outer city. The areas are constituted by a large number of concentrated, gated residential communities. These communities usually have less than four gates which connect with urban roads, resulting in a large proportion of road segments in this area 'internal' roads, which are not directly connected with urban streets. Therefore, the overall density in this area is lower than that of the inner city. The third cluster is facilities in the newly developed area of the city. Residential communities in this area are like isolated enclaves, with few adjacency communities, in that they are all newly developed. The size of urban block is the largest among the three so that their overall density is the lowest.

In the second phase, K-means algorithm is performed on each group of facilities generated in the first phase, based on three local-scale spatial properties, NAIN_Loc, NACH_Loc and DENS_Loc. For facilities in the inner city and those in the outer city, the second phase clustering generates five clusters for each of them. For facilities in the newly developed area, three clusters are generated. Figure 3 shows the distribution of facilities in each group and spatial properties of each cluster centre. The detail of these facilities will be discussed in the following section with their performance on social participation.

First phase: clusters at global scale



Second phase: clusters at local scale

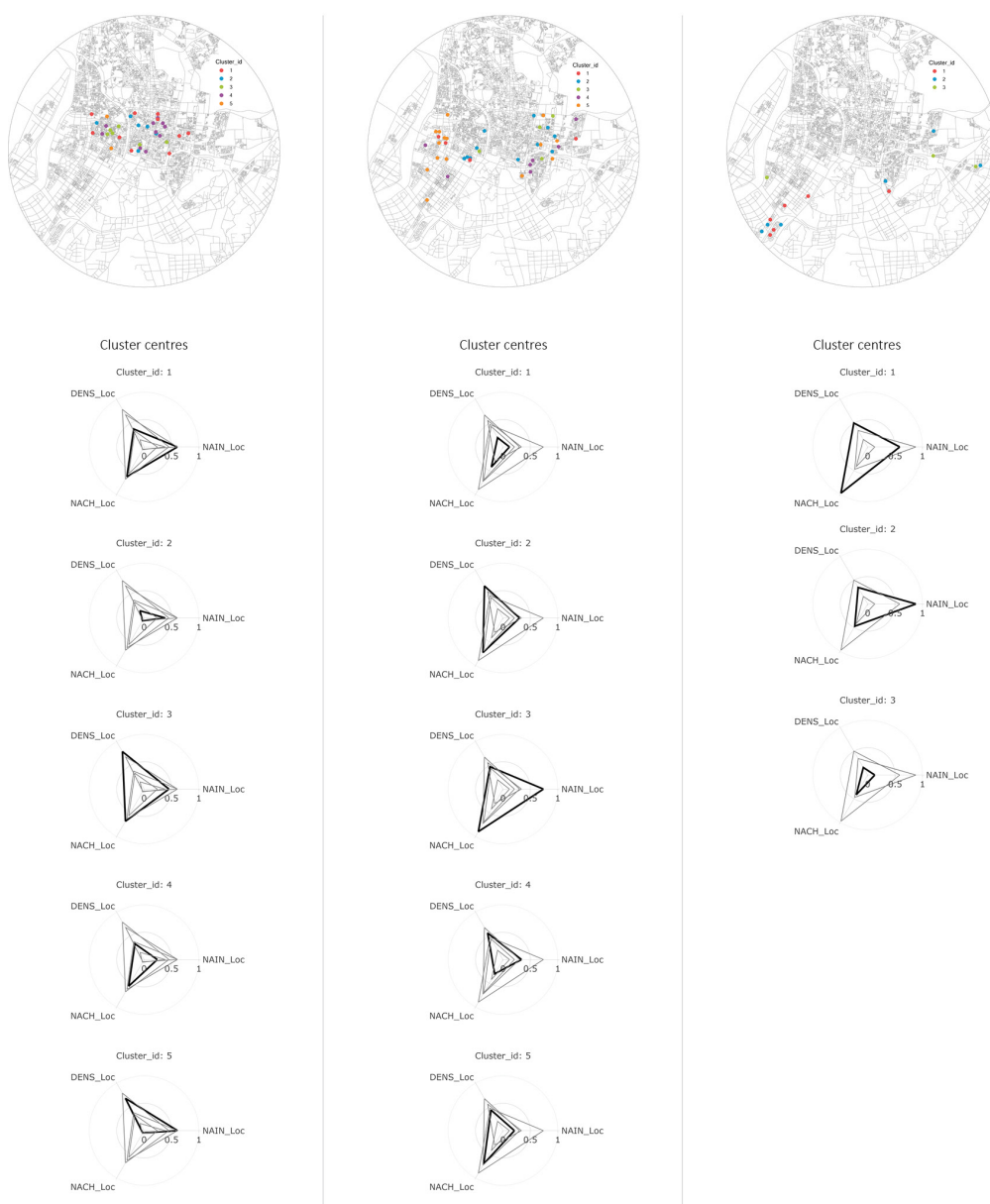


Figure 3: Results of two-phase spatial clustering on care facilities

4.2 Social participation of care facilities

The heatmap in Figure 4 demonstrates the overall distribution of social activities in 91 facilities from May 1st to December 31st in 2020, where the x-axis is facilities and y-axis is the timeline. Each cell in the heatmap represent one day in one facility. The grayscale of one cell represents the total number of people participating in social activities in that facility at that day. We can tell from the heatmap that some facilities have social activities throughout the year while others are only active in specific months. Besides, the number of people participating in social activities in each facility at each day also varies significantly, which is results of some large-scale collective social activities, such as rehearsals of singing and dancing clubs before festivals or special events.

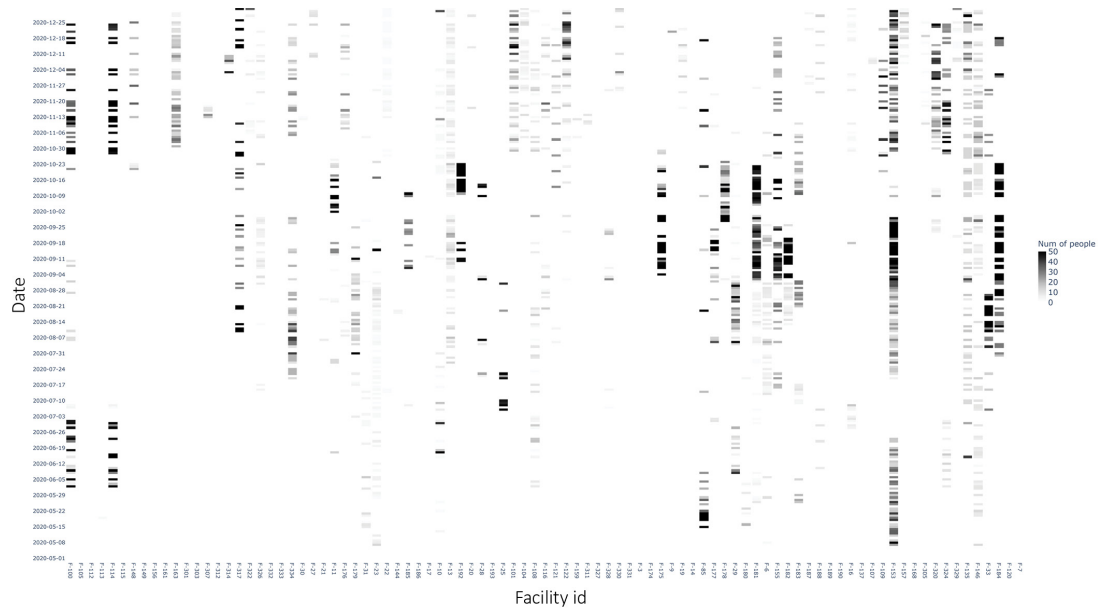


Figure 4: Records of social activities in all care facilities during May 1st to December 31st in 2020

The three social variables we proposed in this paper, long-term consistency (LT_Con), short-term consistency (ST_Con) and average capacity (Ave_Cap), are trying to capture overall patterns of participation and avoiding the influence of accidental events. Figure 5 shows the statistical and geographical distribution of three social variables in all facilities. For LT_Con, it ranges from zero to eight and the median value is two, showing that half of the cases only have two months or less during which social activities were recorded. As for ST_Con, the maximum value is eighteen and median is four, meaning that a facility can have at most eighteen days in one month with social activities recorded, which is almost all the workdays in a month. Half of the cases only have four days or less in a month with social participation. The median value of Ave_Cap is around seven, indicating that throughout all the active days, around half of the facilities have in average seven records of social activities every day.

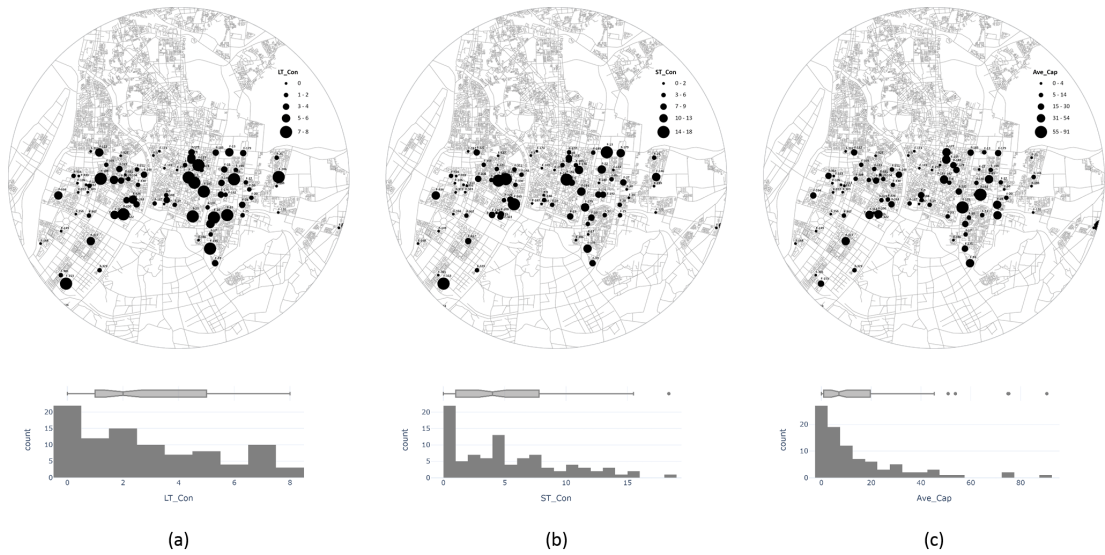


Figure 5: Statistical and geographical distribution of social variables: (a) LT_Con, (b) ST_Con, (c) Ave_Cap

4.3 Socio-spatial relations

(1) Facilities in the inner city

For care facilities in the inner city, five spatial clusters are generated at local scale (see Figure 3). The distribution of three social variables in five spatial clusters is demonstrated by bar charts in Figure 6. ANOVA tests find significant differences among spatial clusters regarding their Long-term Consistency ($F(4, 29) = 3.985, p = 0.011$). No statistically significant difference is found for Short-term Consistency ($F(4, 29) = 0.996, p = 0.425$) and Average capacity ($F(4, 29) = 1.341, p = 0.278$). For post hoc comparison, as shown in Table 2 (b), significant mean differences are detected only between cluster 1 and 2, cluster 2 and 4 in Long-term Consistency.

Facilities in cluster 2 are featured by high local Integration values, but very low Density and Choice values. Cases in both cluster 1 and 4 have high local Choice values. It seems to indicate that for facilities in the inner city, local Choice value (as an indicator of local-scale through-movement) is an important factor that providing care facilities with social participants in the long term.

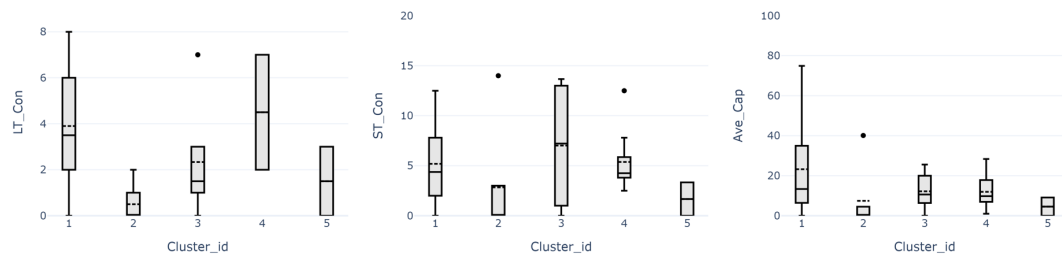


Figure 6: Distribution of social variables in spatial clusters of facilities in the inner city



Table 2: ANOVA test (a) and post hoc comparison (b) for spatial clusters of facilities in the inner city

(a)

	df	LT_Con			ST_Con			Ave_Cap		
		Mean sqr	F	Sig.	Mean sqr	F	Sig.	Mean sqr	F	Sig.
Between Groups	4	18.787	3.985*	0.011	19.102	0.996	0.425	337.747	1.341	0.278
Within Groups	29	4.715			19.173			251.819		
Total	33									

(b)

Cluster_id		LT_Con		ST_Con		Ave_Cap	
		Mean Diff	Sig.	Mean Diff	Sig.	Mean Diff	Sig.
1	2	3.400*	.038	2.354	0.834	15.792	0.326
1	3	1.567	.634	-1.829	0.926	11.042	0.665
1	4	-.600	.971	-0.187	1.000	11.299	0.514
1	5	2.400	.616	3.520	0.836	18.675	0.559
2	3	-1.833	.594	-4.183	0.476	-4.750	0.985
2	4	-4.000*	.010	-2.541	0.793	-4.493	0.981
2	5	-1.000	.979	1.167	0.997	2.883	0.999
3	4	-2.167	.324	1.642	0.949	0.257	1.000
3	5	.833	.989	5.349	0.573	7.633	0.976
4	5	3.000	.402	3.708	0.809	7.376	0.974

*. The mean difference is significant at the 0.05 level.

(2) Facilities in the outer city

As for facilities located in areas of the outer city, five spatial clusters are generated at local scale (Figure 3). ANOVA tests find significant differences among spatial clusters regarding their Long-term Consistency ($F(4, 37) = 5.695, p = 0.001$) and Short-term Consistency ($F(4, 37) = 3.391, p = 0.018$). No statistically significant difference is found for Average capacity ($F(4, 37) = 0.889, p = 0.480$). Results of post hoc comparison show significant mean differences among several pairs of spatial clusters in both LT_Con and ST_Con. For LT_Con, the mean value of cluster 1 is lower than those of cluster 2, 3 and 4. The mean value of cluster 5 is lower than cluster 2 and 4. In general, as demonstrated by Figure 7, facilities in cluster 1 and 5 have lower LT_Con values than those of cluster 2, 3 and 4. As for ST_Con, cluster 3 is significantly higher than cluster 1 and 5.

Spatial properties of cluster centres in Figure 3 show that cluster 1 and 5 have the lowest local Integration values among all the groups, which seems to suggest that local-scale Integration, i.e., closeness centrality, as an indicator of to-movement, is an influencing factor for the long-term consistency of care facilities in the outer city. Cluster 3 is the most advantageous group in terms of spatial properties, with highest values in all three variables, whereas cluster 1 is the least advantageous. Comparing the overall distribution of ST_Con and LT_Con in five spatial groups in Figure 7, cluster 2, 3 and 4 outweigh cluster 1 and 5 in both cases. It seems that Integration plays an important role in facilitating both long-term and short-term consistency for social participation of facilities in the outer city.

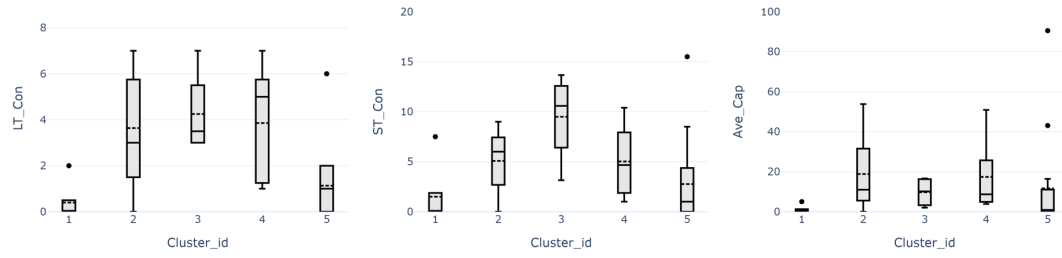


Figure 7: Distribution of social variables in spatial clusters of facilities in the outer city

Table 3: ANOVA test (a) and post hoc comparison (b) for spatial clusters of facilities in the outer city

(a)

	df	LT_Con			ST_Con			Ave_Cap		
		Mean sqr	F	Sig.	Mean sqr	F	Sig.	Mean sqr	F	Sig.
Between Groups	4	22.330	5.695*	0.001	48.145	3.391*	0.018	324.002	0.889	0.480
Within Groups	37	3.921			14.200			364.621		
Total	41									

(b)

Cluster_id		LT_Con		ST_Con		Ave_Cap	
		Mean Diff	Sig.	Mean Diff	Sig.	Mean Diff	Sig.
1	2	-3.236*	.034	-3.582	0.410	-17.814	0.429
1	3	-3.850*	.046	-7.994*	0.024	-8.747	0.959
1	4	-3.457*	.038	-3.520	0.510	-16.373	0.591
1	5	-.733	.951	-1.267	0.965	-10.635	0.816
2	3	-.614	.984	-4.412	0.284	9.067	0.925
2	4	-.221	.999	0.063	1.000	1.441	1.000
2	5	2.503*	.023	2.316	0.539	7.180	0.876
3	4	.393	.998	4.474	0.338	-7.626	0.968
3	5	3.117	.059	6.727*	0.024	-1.887	1.000
4	5	2.724*	.036	2.253	0.689	5.739	0.964

*. The mean difference is significant at the 0.05 level.

(3) Facilities in the newly developed areas

Three local-scale spatial clusters are generated in facilities located in the newly developed areas in the city. ANOVA tests show significant differences among spatial clusters regarding their Long-term Consistency ($F(2, 12) = 5.052, p = 0.026$) and Short-term Consistency ($F(2, 12) = 7.843, p = 0.007$). No statistically significant difference is found for Average capacity ($F(2, 12) = 1.754, p = 0.215$). Post hoc comparisons find mean value of LT_Con of cluster 2 is higher than those of cluster 3. Mean values of ST_Con of both cluster 1 and 2 are higher than those of cluster 3. Referring to Figure 3, the major difference between cluster 3 and cluster 1 or 2 is Integration and Density values at local scale. We can assume local-scale Integration and Density impact both long- and short-term consistency of social activities in facilities in the newly developed areas. Choice seems not to be an influential factor in these facilities, because Choice values of both cluster 2 and 3 are low but social performance of cluster 2 is much better than that of cluster 3.

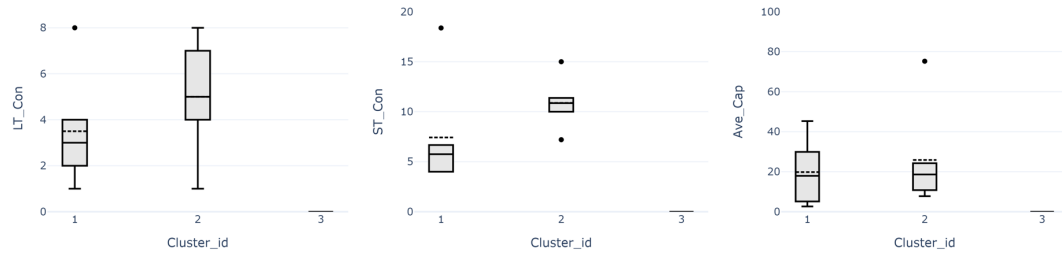


Figure 8: Distribution of social variables in spatial clusters of facilities in the newly developed areas

Table 4: ANOVA test (a) and post hoc comparison (b) for spatial clusters of facilities in the newly developed areas

(a)

	df	LT_Con			ST_Con			Ave_Cap		
		Mean sqr	F	Sig.	Mean sqr	F	Sig.	Mean sqr	F	Sig.
Between Groups	2	25.050	5.052*	0.026	118.460	7.843*	0.007	681.601	1.754	0.215
Within Groups	12	4.958			15.104			388.645		
Total	14									

(b)

Cluster_id		LT_Con		ST_Con		Ave_Cap	
		Mean Diff	Sig.	Mean Diff	Sig.	Mean Diff	Sig.
1	2	-1.500	0.494	-3.458	0.307	-6.072	0.857
1	3	3.500	0.107	7.423*	0.047	19.809	0.362
2	3	5.000*	0.020	10.881*	0.005	25.881	0.194

*. The mean difference is significant at the 0.05 level.

5 DISCUSSION

This study reveals that local-scale spatial properties could influence participation patterns of social activities in community-based care facilities, and the way local-scale spatial properties exert influence varies in different global-scale spatial contexts. In the inner city, higher values of Choice at local-scale relate to higher values of long-term consistency (LT_Con), whereas in the outer city and newly developed areas, locally integrated facilities tend to be frequented more often in both the long- and short-term than less well integrated facilities. This variation also indicates that although the scale of older people's social behaviour/movement is localised, i.e., older people walking to care facilities in their neighbourhood, it can still, to some extent, be the outcome of joint influence of both global- and local-scale spatial contexts.

As for possible interpretations of the finding discussed above, we propose that it might relate to differentiated movement patterns of older people in their everyday life in the inner and outer city (including newly developed areas), which are shaped largely by the differentiated spatial structure of residential communities in these areas. A prominent difference between residential communities in the inner and outer city is that large-scale gated residential communities are rare in the former context, but very common in the later one, especially in the newly developed areas. These communities usually occupy a whole street block, with limited numbers of entrances

connected to urban streets. In this context, most land-uses or public amenities are aggregated either at the intersections of urban streets, or in central areas inside communities. Destinations of older people's everyday movements are clear and 'centralised'. Therefore, to-movement with clear destinations is a major movement pattern in this context. However, in the inner city, gated residential communities are small, or residential buildings are located directly on urban streets without any gates. People have easy access to urban streets where various local amenities are 'evenly' distributed. In this context, destinations of people's everyday movements are diverse, spatially dispersed, and their trajectories can be random or complex in urban fabric. In other words, through-movements without clear destinations constitute a large proportion of older people's local movements in the dense inner city.

With differentiated movement patterns in people's everyday life, advantageous spatial properties for care facilities in the inner or outer city are different. In the inner city, facilities with higher local Choice value means they are more likely to be passed through by elderly people who visit a variety of destinations in their daily life. This increases the awareness of care facilities in local older people's mind and provides consistent pass-byers in the long term, thus supporting long-term social participation in care facilities. As for the outer city or the newly developed areas, facilities with higher local Integration value indicates that they are likely to be close to the 'centre' of local communities where commercial or other amenities are aggregated, being the destination of local people's to-movements. This can also improve people's social participation in care facilities in both long- and short-term.

It is also worth noting that, for average capacity (Ave_Cap), no statistically significant differences are observed among all spatial clusters. This may imply that the spatial model used in this study is inadequate to detect proper spatial factors which impact this social variable, or it can also be interpreted as urban-scale spatial factors are not effective in determining how many social participants a facility can absorb on daily basis. The average capacity of a care facility may be more related to architectural factors, such as the overall building areas, or more specifically, the total number of public seats and rooms in facilities. These will be addressed in future research.

6 CONCLUSION

This paper introduces spatial network model into the study of elderly care facilities, to quantitatively illustrate spatial relations between care facilities and urban communities, and investigate spatial impact on patterns of social participation in care facilities. Taking 91 care facilities as cases in the Chinese city of Nanjing, altogether with data of social participation in the year of 2020, the study finds local-scale spatial properties could influence participation patterns of social activities in community-based care facilities, and the way local-scale spatial properties exert influence varies in different global-scale spatial contexts. In the inner city with dense street networks, facilities with higher local choice values are likely to have consistent social participation in the long term, whereas in the outer city or newly developed areas, this



happens in facilities with higher local integration values. The paper proposed that differentiated to- and through-movement patterns of people's daily life in those areas, which are shaped by spatial structures of residential communities, might be an underlying mechanism to explain the socio-spatial relations in care facilities. Findings of this paper provide empirical evidence for policy makers and urban planners to optimise spatial distribution of care facilities in various urban contexts in the future.

Considering limitations of this study, two additional points will be addressed in the future. One is that various types of social activities will be identified and categorised according to their spatial and behavioural traits, which might lead to more targeted policy implication. The other one is to incorporate architectural factors (e.g., building areas, furniture arrangements and etc.) into the analytic framework, which can be critical to explain the variation of facilities' capacity in absorbing social participants.

REFERENCES

- Aday, R. H., Wallace, B. & Krabill, J. J. (2018). 'Linkages Between the Senior Center as a Public Place and Successful Aging', *Activities, Adaptation & Aging*, 1-21.
- Ashida, S. & Heaney, C. A. (2008). 'Social Networks and Participation in Social Activities at a New Senior Center: Reaching Out to Older Adults Who Could Benefit the Most', *Activities, Adaptation & Aging*, 32, 40-58.
- Bassuk, S. S., Glass, T. A. & Berkman, L. F. (1999). 'Social disengagement and incident cognitive decline in community-dwelling elderly persons', *Annals of internal medicine*, 131, 165-173.
- Beyer, G. H. & Nierstrasz, F. H. J. (1967). *Housing the aged in Western countries programs, dwellings, homes, and geriatric facilities*. Ithaca, NY, Bouwcentrum, Rotterdam, and the Center for Housing and Environmental Studies.
- Bitzan, J. E. & Kruzich, J. M. (1990). 'Interpersonal Relationships of Nursing Home Residents', *The Gerontologist*, 30, 385-390.
- Brun, M., Sima, C., Hua, J., Lowey, J., Carroll, B., Suh, E. & Dougherty, E. R. (2007). 'Model-based evaluation of clustering validation measures', *Pattern Recognition*, 40, 807-824.
- Cheng, Y., Rosenberg, M. W., Wang, W. Y., Yang, L. S. & Li, H. R. (2012). 'Access to residential care in Beijing, China: making the decision to relocate to a residential care facility', *Ageing & Society*, 32, 1277-1299.
- Corden, A. & Wright, K. 1993. Going into a home: where can an elderly person choose? *Population Matters: The Local Dimension*. Paul Chapman London.
- De Syllas, J. Domestic Asylum: a study of eleven local authority hostels for mentally handicapped people. Proceedings of the Second International Space Syntax Symposium, 1999.
- Gil, J. 2015. Examining "Edge Effects": Sensitivity of Spatial Network Centrality Analysis to Boundary Conditions. *Proceedings of the 10th International Space Syntax Symposium*.
- Hickerson, B., Moore, A., Oakleaf, L., Edwards, M., James, P. A., Swanson, J. & Henderson, K. A. (2008). 'The Role of a Senior Center in Promoting Physical Activity for Older Adults', *Journal of Park & Recreation Administration*, 26.
- Hillier, B., Yang, T. & Turner, A. (2012). 'Normalising least angle choice in Depthmap-and how it opens up new perspectives on the global and local analysis of city space', *Journal of Space syntax*, 3, 155-193.



- Hutchinson, S. L. & Gallant, K. A. (2016). 'Can Senior Centres be Contexts for Aging in Third Places?', *JOURNAL OF LEISURE RESEARCH*, 48, 50-68.
- Jiangsu Provincial Government 2018. Report on the information and development of undertakings for ageing population in Jiangsu Province in 2017.
- Kadowaki, L. & Mahmood, A. (2018). 'Senior Centres in Canada and the United States: A Scoping Review', *Can J Aging*, 37, 420-441.
- Krout, J. A. (1997). 'Senior Center Programming and Frailty Among Older Persons', *Journal of Gerontological Social Work*, 26, 19-34.
- Levasseur, M., G  n  reux, M., Bruneau, J. F., Vanasse, A., Chabot,   ., Beaulac, C. & B  dard, M. M. (2015). 'Importance of proximity to resources, social support, transportation and neighborhood security for mobility and social participation in older adults: Results from a scoping study', *BMC Public Health*, 15, 503-503.
- Li, X. & Sailer, K. 2021. Spatial network morphology and social integration of the elderly: The socio-spatial 'embeddedness' of community-based elderly care facilities. *ISUF2021*. Glasgow.
- Marshall, S., Gil, J., Kropf, K., Tomko, M. & Figueiredo, L. (2018). 'Street Network Studies: from Networks to Models and their Representations', *Networks and Spatial Economics*.
- Mens, N. & Wagenaar, C. (2010). *Health Care Architecture in the Netherlands*. Rotterdam, NAI Publishers.
- Pardasani, M. & Thompson, P. (2010). 'Senior Centers: Innovative and Emerging Models', *Journal of Applied Gerontology*, 31, 52-77.
- Peponis, J., Bafna, S. & Zhang, Z. (2008). 'The Connectivity of Streets: Reach and Directional Distance', *Environment and Planning B: Planning and Design*, 35, 881-901.
- Reed, J., Payton, V. R. & Bond, S. (1998). 'The importance of place for older people moving into care homes', *Social Science & Medicine*, 46, 859-867.
- Rosenberg, B. C. (2015). 'Social spaces for seniors: Exploring seniors' centres and clubs in Australia', *Journal of Sociology*, 51, 464-477.
- Satopaa, V., Albrecht, J., Irwin, D. & Raghavan, B. Finding a "kneedle" in a haystack: Detecting knee points in system behavior. 31st International Conference on Distributed Computing Systems Workshops, 2011 2011 Minneapolis, MN, USA. IEEE, 166-171.
- Schorr, A. V., Iecovich, E., Alfasi, N. & Shamai, S. (2017). 'Socio-Spatial Integration of Older Adults in Four Types of Residential Environments in Israel', *JOURNAL OF APPLIED GERONTOLOGY*, 36, 1243-1271.
- Takahashi, K., Tamura, J. & Tokoro, M. (1997). 'Patterns of social relationships and psychological well-being among the elderly', *INTERNATIONAL JOURNAL OF BEHAVIORAL DEVELOPMENT*, 21, 417-430.
- Turner, A. (2007). 'From axial to road-centre lines: a new representation for space syntax and a new model of route choice for transport network analysis', *Environment and Planning B: Planning and Design*, 34, 539-555.
- Turner, K. W. (2004). 'Senior Citizens Centers: What they offer, who participates, and what they gain', *Journal of Gerontological Social Work*, 43, 37-47.
- Van Steenwinkel, I., De Casterl  , B. D. & Heylighen, A. (2017). 'How architectural design affords experiences of freedom in residential care for older people', *Journal of aging studies*, 41, 84-92.
- Walker, J., Bisbee, C., Porter, R. & Flanders, J. (2004). 'INCREASING PRACTITIONERS' KNOWLEDGE OF PARTICIPATION AMONG ELDERLY ADULTS IN SENIOR CENTER ACTIVITIES', *Educational Gerontology*, 30, 353-366.
- Wang, F., Zhang, W. & Hui, J. (2017). 'Module Construction & Network Implantation: A Study on the Present Situation and Configuration Mode of Home Care Service Facilities in Urban Community', *NEW ARCHITECTURE*, 19-23.



Wright, F. D. (1995). *Opening Doors: a case study of multi-purpose residential homes*. HM Stationery Office.