land

MDPI

Article

Time Allocation and the Activity-Space-Based Segregation of Different Income Groups: A Case Study of Nanjing

Hui Wang [1], Mei-Po Kwan [2], Mingxing Hu [3,*], Junheng Qi [3], Jiemin Zheng [3] and Bin Han [3]

[1] College of Landscape Architecture, Nanjing Forestry University, Nanjing 210037, China
[2] Department of Geography and Resource Management, Institute of Space and Earth Information Science, The Chinese University of Hong Kong, Shatin, Hong Kong, China
[3] School of Architecture, Si Pailou Campus, Southeast University, Nanjing 210096, China
* Correspondence: 101009930@seu.edu.cn

Abstract: Time allocation is closely related to life quality and is a potential indicator of urban space utilization and sociospatial differentiation. However, existing time allocation studies focus on how time is allocated to various activities but pay less attention to where individuals allocate their time. In the context of China's transformation, this study examines the differences in time allocation in different urban spaces between low- and non-low-income groups based on two methods, descriptive statistics and social area analysis. The results show that low-income participants' daily activities (especially work) are highly dependent on the central city area. However, they are at a disadvantage in accessing the central city area. Nevertheless, non-low-income individuals have diversified activity spaces and can better choose locations according to the purpose of activities and make fuller use of various types of urban areas. This study indicates that there are social differences in time allocation and urban space utilization among different income groups. The results obtained with regression models reveal that in addition to income, activity characteristics and built environment characteristics are significant factors affecting the differences. Social policies should support the equitable distribution of urban resources for different social groups, especially for vulnerable groups who live in affordable housing.

Keywords: low income; activity space; time allocation; sociospatial differentiation; China

Citation: Wang, H.; Kwan, M.-P.; Hu, M.; Qi, J.; Zheng, J.; Han, B. Time Allocation and the Activity-Space-Based Segregation of Different Income Groups: A Case Study of Nanjing. *Land* **2022**, *11*, 1717. https://doi.org/10.3390/land11101717

Academic Editor: Fabrizio Battisti

Received: 12 September 2022
Accepted: 1 October 2022
Published: 4 October 2022

1. Introduction

It has been recognized that time plays an important role in the travel and activity behavior of individuals [1–4], which is related to life quality and important for the development of transport and land use policies [5–7]. Time is a resource, and people allocate time to different activities and places under various constraints, such as the urban built environment, individual socioeconomic attributes and personal preferences [1,8,9]. Vulnerable groups may tend to spend their time in specific spaces due to low mobility, limited employment skills and physical limitations. [10–12]. In contrast, mainstream groups are more likely to make full use of urban spaces and resources. Therefore, studying how individuals allocate time in different urban spaces can shed some light on the complex relationship between individual activities, urban space utilization and urban spatial structure, which is related to social equity and spatial justice [13].

Sociospatial differentiation, which reflects the inequality of different social groups in urban spatial distribution, is an important topic in the field of urban planning, geography and sociology. While conventional segregation studies focus on residential neighborhoods [14,15], over the past two decades, the "new mobilities" paradigm has been proposed to emphasize that the study of segregation should integrate human mobility and consider the temporal dimension [16–19]. People of different social groups may not only spend their time in residential areas but also allocate their time to non-residential areas for

work, leisure, shopping and other personal activities [20]. These out-of-home experiences, reflecting the individual's actual use of urban space, may enhance or lessen the degree of isolation that individuals experience in their daily lives [18,20–24].

In recent years, an increasing number of studies have been conducted to examine people's utilization of different urban forms and sociospatial differentiation from the perspective of activity space [13,23–27]. For instance, Kwan [28] found that women face higher levels of daytime fixity constraints when accessing jobs and urban opportunities. Wang et al. [29] showed that public housing residents spend more time outside the home than private housing residents, and the difference is mainly determined by working hours. Krivo et al. [30] noted that economically disadvantaged people conduct their daily activities mainly in "local areas" that are similar to the disadvantaged contexts where they reside, thereby reinforcing social isolation. Silm and Ahas [31] employed data on mobile phone use to compare variations in segregation indices on different time scales, finding that people are more segregated at night and on weekends than in the daytime and on weekdays. These studies primarily focus on the geographical distribution of the activity space and access to urban opportunities of different social groups but pay less attention to where individuals spend their time.

According to the conceptual framework of time geography introduced by Hägerstrand [1], an individual can only be in one place at a specific time and thus space and time are inseparable. Time is a limited resource, and people may allocate their limited time to different activities and places due to their different lifestyles, accessibility and time-space constraints. Income is one of the most important variables that stratifies individuals in terms of activity-travel behavior [11]. Compared with non-low-income individuals, low-income individuals have been reported to have lower mobility, travel shorter distances, make fewer trips and be more dependent on public transport [32]. Therefore, it is likely that different income groups may present different patterns of activity time allocation and urban space utilization.

Chinese urban structures have a unique history of development. Driven by economic reform and the opening-up policy of the 1980s, China's urbanization level rapidly increased from 17.92% in 1978 to 64.72% in 2021 (National Bureau of Statistics of China, 2021). Most Chinese cities have experienced rapid transformation in their spatial structure in terms of the expansion of urban areas, the formation of central business districts (CBDs), the reconstruction of the traditional inner city and suburbanization. These changes have resulted in a more uneven distribution of urban spatial resources and population. On the one hand, central cities have the best urban resources (e.g., public transport, schools, shopping malls and hospitals) and job opportunities in the tertiary sector [33,34]. On the other hand, the suburbanization of high-end industries has created many knowledge-intensive job opportunities, mainly for highly skilled people. Moreover, high-quality country parks are built in the outer suburbs to improve the quality of life of residents. Previous studies primarily consider static population or housing data (i.e., demolition data, housing price data, census data, neighborhood committee data) and adopt the method of social area analysis to analyze the structure of urban spatial differentiation. However, to date, few have analyzed the use of urban space by different income groups from the perspective of time allocation.

Accordingly, we argue that two research gaps in the existing time allocation research can be identified and should be addressed. On the one hand, although some scholars have begun to pay attention to the issue of time allocation in activity-space-based social isolation, these studies mainly focus on the time of different activities and pay less attention to the time distribution in the daily life of different social groups in different geographic spaces. On the other hand, in the context of China's transformation, the utilization of urban space by different income groups, which is closely related to the optimization of urban spatial structure and the fairness of resource distribution, has not been fully examined.

To fill in the research gaps, we conducted a case study of Nanjing to answer the following questions: how do people of different income groups allocate their time in

different urban spaces? What is the agglomeration pattern of activities of different income groups in urban space? What factors influence individuals' different activity times in different urban spaces? Quantifying and characterizing urban space utilization and activity patterns reveal the spatial distribution of resources and people's preferences, which can guide the optimization and sustainable development of urban space.

2. Methods and Data Collection

2.1. Study Area and Data Collection

The study area for this research is Nanjing (Figure 1), which is the capital of Jiangsu Province in China and the core area of the Yangtze River Delta. It covers an area of 4,723 square kilometers and had a total population of 7.09 million in 2019. In general, the urban area of Nanjing can be divided into three parts according to the distance of an area from the CBD: the inner city, the inner suburb and the outer suburb. The inner city and inner suburb make up the central area of the city and are called the main city center, while the outer cities are considered suburban areas. Like most cities in China, the Nanjing urban space grew out of the gradual expansion of the inner city. Therefore, the spatial distribution of its urban resources is very uneven, which is reflected in the high-quality public service facilities and tertiary industry employment opportunities being highly concentrated in the inner city and the inner suburb.

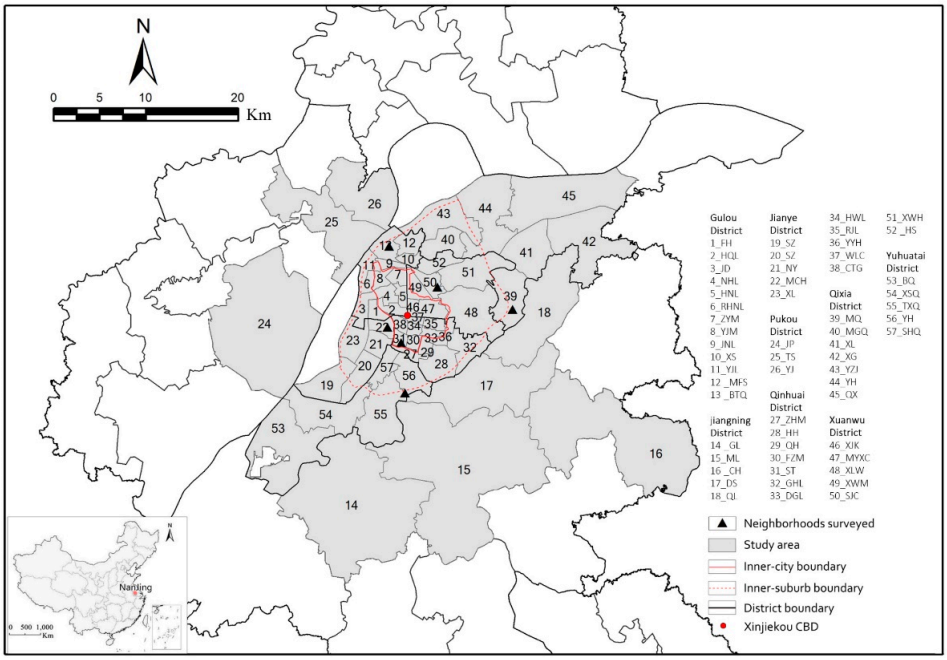


Figure 1. The geographic location of the study area and surveyed neighborhoods in Nanjing, China.

The data for this study come from an activity diary dataset collected by the lead author through a questionnaire survey using stratified random sampling in 2017. The survey sampled participants from six typical neighborhoods of various types located in different districts of Nanjing. A stratified random sampling method was used to conduct the survey on the selected communities in Nanjing. The questionnaire included the socioeconomic attributes of the respondents and their activity diaries for two consecutive days (one weekday and one weekend day).

Based on the international standard poverty line and the per capita disposable income of Nanjing in 2016, respondents with a per capita monthly income of CNY 2000 were defined as low-income residents. Considering that this study focuses on the differences in the characteristics of daily activity space between low-income and other income groups (including middle- and high-income groups), the rest of the respondents were classified as the non-low-income group. Among the 774 valid questionnaires, 424 were low-income

residents and 350 were non-low-income residents. In total, 4,655 records of participants' out-of-home activities were extracted as research data in this study.

In the dataset, respondents' socioeconomic attributes included gender, age, monthly household income, household size, car ownership, education, housing type and employment status. The two-day activity diary provided detailed spatiotemporal information on individual activities during the survey days. For each activity, the respondents were asked to report the type, location and start and end times of activities. Out-of-home activities were extracted and classified into four types: work activities, shopping activities, leisure activities and others (including going to the hospital, taking care of children, going to the post office and other personal matters). There are 57 subdistricts with records of respondents' activities, and these subdistricts are shown in Figure 1.

2.2. Method

Descriptive statistics are a common method to analyze individual time allocation and activity arrangement, generally by calculating the time individuals allocated to different activities and locations in a specific period (such as a day, a week, a month, etc.). In this study, the activity time of individuals of different income groups in different types of urban spaces (i.e., the inner city, the inner suburb and the out suburb) was firstly counted. The longer individuals stay in a particular space, the more they make use of that space in their daily lives. Moreover, an ANOVA test was used to compare these indicators of spatio-temporal behavior between the two groups.

However, the same allocation of time in the same place by two different individuals does not mean that the place is equally important to them because the total time people spent outside the home differs among individuals. Therefore, this study adopted the location quotient and social area analysis methods to analyze the utility of different income groups in different urban spaces and the overall distribution pattern of daily activities in the city.

First, the location quotient is used to analyze the utility of different urban forms of different income groups, and the analysis scope is 57 streets with activity records. The location quotient is adopted to measure the spatial distribution of the activities of a resident with a certain level of income in a certain area, and its calculation formula is as follows:

$$LQ_{ij} = \frac{Q_{ij} / \sum_{i=1}^{n} Q_{ij}}{P_i / \sum_{i=1}^{n} P_i}$$

where *LQij* is the location quotient of the spatial agglomeration of activities *i* of an income group, *LQij* is the duration of activities *i* of an income group in area j in a day and Pi is the sum of all out-of-home activities of the income group in area j in a day.

To understand the spatial agglomeration of activity time of different income groups on different interview days, this study calculates 16 activity time location quotients in Table 1.

Then, to further understand the utilization of different urban spaces by different income groups, this study adopted the method of social area analysis to understand the overall time allocation of people's daily activities in urban spaces. Social area analysis was initiated by Shevky and Williams [35] in a study of Los Angeles, and it has become one of the most common methods used to analyze the urban spatial structure and neighborhood-based sociospatial differentiation [36–38]. Specifically, first, the spatial distribution of activities of different income groups is summarized by factor analysis. Then, conceptual models are drawn based on the clustering results to summarize the distribution structure of the activity space of different income groups in urban space.

OLS regression is used to analyze the influencing factors of participants' activity time allocation on different diary days. To understand the impact of income on the distribution of activity time, this study first constructed a simple model with only income variables and then added other variables to observe the impact of other variables on the allocation of individual daily activity time in different spaces. Since individuals participating on different diary days were significantly different, we divided the model into two groups

according to weekdays and weekends, and then the influencing factors of each group on different activities of individuals were analyzed.

Table 1. Spatial distribution of daily activities and measurement indicators.

Level-One Variable	Level-Two Variable
(1) Spatial distribution of working activities	1. LQ of weekday-working-activities of the low-income group 2. LQ of weekday-working-activities of the non-low- income group 3. LQ of weekend-working-activities of the low-income group 4. LQ of weekend-working-activities of the non-low- income group
(2) Spatial distribution of shopping activities	5. LQ of weekday-shopping-activities of the low- income group 6. LQ of weekday- shopping -activities of the non-low-income group 7. LQ of weekend- shopping -activities of the low- income group 8. LQ of weekend- shopping -activities of the non-low-income group
(3) Spatial distribution of leisure activities	9. LQ of weekday-leisure-activities of the low-income group 10. LQ of weekday- leisure -activities of the non-low-income group 11. LQ of weekend- leisure -activities of the low- income group 12. LQ of weekend- leisure -activities of the non-low-income group
(4) Spatial distribution of other out-of-home activities	13. LQ of weekday-others-activities of the low-income group 14. LQ of weekday-others-activities of the non-low- income group 15. LQ of weekend-others-activities of the low-income group 16. LQ of weekend-others-activities of the non-low- income group

2.3. Descriptive Statistics

Table 2 shows the socioeconomic attributes of the respondents. In general, there are significant differences between low- and non-low-income respondents in socioeconomic attributes except household structure. Compared with the non-low-income respondents, the low-income respondents have a higher proportion of women and elderly, larger family sizes, lower levels of education and significantly higher unemployment rates. There are obvious differences in housing types among individuals in different income groups. The main housing types for low-income people are affordable housing and rental housing, while the non-low-income respondents mainly live in *danwei* housing and commercial housing. In terms of car ownership, the low- and non-low-income respondents have, on average, 0.1 and 0.4 cars, respectively, indicating that the mobility of low-income residents is lower.

Table 2. Sample characteristics.

Variables	Classification	Low-Income (N = 424)		Non-Low-Income (N = 350)		Total (N = 774)		*p* Value
		N	%	N	%	N	%	
Gender	Male	197	46.5	203	58	400	51.7	0.001 ***
	Female	227	53.5	147	42	374	48.3	
Age	16–29	47	11.1	76	21.7	123	15.9	0.000 ***
	30–59	237	55.9	192	54.9	429	55.4	
	≥60	140	33	82	23.4	222	28.7	
Education	Middle school or lower	250	59	115	32.9	365	47.2	0.000 ***
	High school	122	28.8	90	25.7	212	27.4	
	College or university or above	52	12.2	145	41.4	197	25.5	
Household structure	Single person	23	5.4	36	10.3	59	7.6	0.640
	Couple alone	97	22.9	74	21.1	171	22.1	
	Two generations	145	34.2	129	36.9	274	35.4	
	Three generations and above	159	37.5	111	31.7	270	34.9	

Table 2. *Cont.*

Variables	Classification	Low-Income (N = 424)		Non-Low-Income (N = 350)		Total (N = 774)		*p* Value
		N	%	N	%	N	%	
Employment status	Employed	208	49.1	248	70.9	571	73.8	0.000 ***
	Not employed (including retired)	216	50.9	102	29.1	203	26.2	
Housing type	Danwei	74	17.5	70	20.0	144	18.6	0.000 ***
	Commercial	36	8.5	64	18.3	100	12.9	
	Rental	102	24.1	83	23.7	185	23.9	
	Affordable housing	212	50.0	133	38.0	345	44.6	
Car ownership (Mean)		0.1	–	0.4	–	0.2	–	0.000 ***

Notes: *** Significant at the 0.01 level.

3. Results

3.1. Differences in Time Allocation in Urban Spaces among Income Groups

Table 3 shows a comparative analysis of the activity time of individuals in different income groups in various urban spaces. Overall, there are significant differences in time allocation among different income groups in the inner suburb and outer suburb, but there is no statistically significant difference in the inner city. From the perspective of time allocation, low-income respondents make the most use of the inner suburb on weekdays and the outer suburb on weekends. However, non-low-income respondents make the most use of the space in the inner suburbs on both weekdays and weekends.

Table 3. Differences in the time distribution of the out-of-home activities among different income groups by urban space (mean value, min).

Urban Form	Activity Type	Weekday		Weekend	
		Non-Low-Income	Low-Income	Non-Low-Income	Low-Income
Inner city	Working	102	79.7	28.6	36.2
	Shopping	3.2 ^{a**}	7.3 ^{b**}	19.1	13.9
	Recreation	15.3	18.3	33	24.3
	Other	11.4	11.2	15.1	13.0
	Total	131.95	116.49	95.77	87.37
Inner suburb	Working	184.4 ^{a***}	127.3 ^{b***}	72.4	67.9
	Shopping	8.5	8.7	21.6	16.8
	Recreation	44.4	34.1	60.6 ^{a*}	45.9 ^{b*}
	Other	17.1	19.9	41.1 ^{a*}	29.3 ^{b*}
	Total	254.37 ^{a***}	189.9 ^{b***}	195.79 ^{a**}	159.9 ^{b**}
Outer suburb	Working	95	87.7	30.5 ^{a**}	59.5 ^{b**}
	Shopping	7.3 ^{a***}	13.3 ^{b***}	16.7	13.4
	Recreation	41.5 ^{a**}	61.0 ^{b**}	64.0	76.3
	Other	14.3	18.7	28.7	23.4
	Total	158.1	180.71	139.92 ^{a**}	172.57 ^{b**}

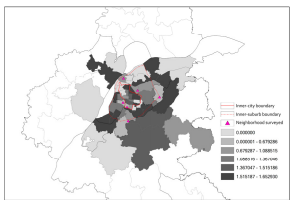
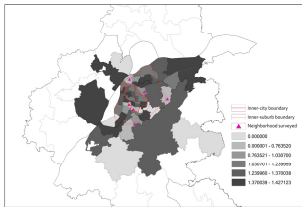
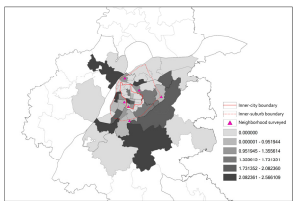
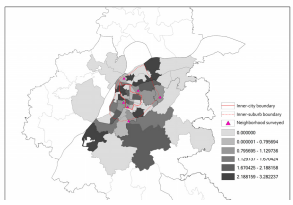
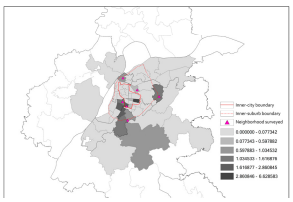
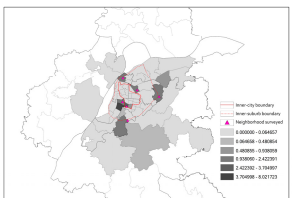
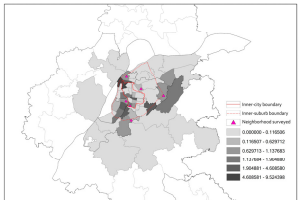
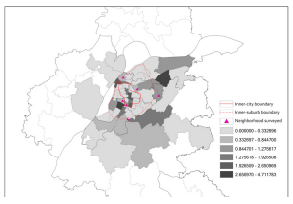
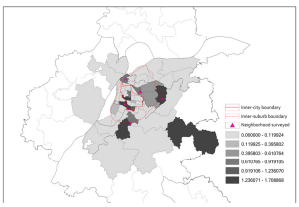
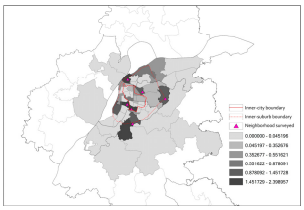
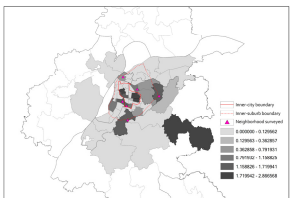
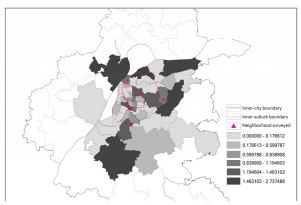
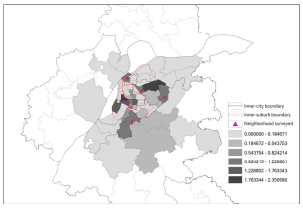
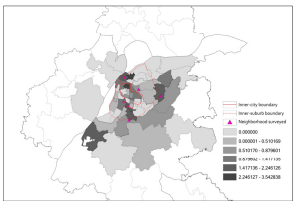
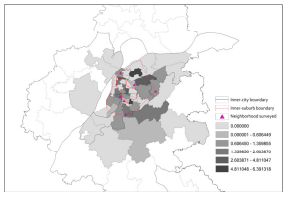
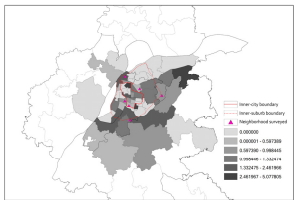
Notes: [a] The difference from the low-income group is statistically significant. [b] The difference from the non-low-income group is statistically significant. * Significant at the 0.10 level. ** Significant at the 0.05 level. *** Significant at the 0.01 level.

In terms of different types of activities, on weekdays, compared with non-low-income respondents, low-income respondents spend more time shopping in the inner city and less time working in the inner suburb, while they spend more time on shopping and leisure in the outer suburb. It is worth noting that both low-income and non-low-income groups allocate the most working time in the inner suburb, indicating that their work activities are highly dependent on the inner suburban spaces. On weekends, low-income

participants spend less time on leisure and other personal activities in the inner suburb but more time working in suburban areas than their counterparts. This indicates that on weekends, low-income groups have more working activities than non-low-income groups, which is possibly because those low-income groups are mainly engaged in low-end tertiary industries with long working hours.

The temporal distribution of the out-of-home activities of low- and non-low-income groups is shown in Table 4. A subdistrict with a higher score means that the low- or non-low-income group uses and relies on this space more. In general, there are obvious differences in the utilization patterns of urban space among different income groups. On weekdays, the work activities of low-income participants are highly concentrated in the main city center and the space near the survey communities, while the high-value spaces are scattered. In contrast, the work activities of the non-low-income group are mainly dispersed in the urban space, and the high-value space is mainly distributed in the inner suburbs and outer suburbs. The neighborhood and the surrounding areas are the main spaces for the shopping, leisure and other personal activities of the two income groups. It is worth noting that the other-personal activities of low-income participants are more concentrated in the main city space than those of the non-low-income group, indicating that low-income people may rely more on the main urban space for their daily life.

Table 4. Temporal distribution of the out-of-home activities of the two income groups by urban space.

	Weekday		**Weekend**	
	Low-Income	**Non-Low-Income**	**Low-Income**	**Non-Low-Income**
Working				
Shopping				
Leisure				
Others				

On weekends, the intensity of work activities of the two income groups decreases, and the distribution is more dispersed than that on weekdays. Compared with non-low-income respondents, low-income respondents' work activities are mainly concentrated in suburban space, but their shopping and leisure activities are mainly distributed in the inner

city and the inner suburbs. In contrast, leisure activities and other personal activities of non-low-income groups show obvious suburbanization characteristics.

3.2. Differences in Urban Space Utility among Income Groups

Social area analysis is adopted to further understand the utility of spaces among income groups. First, factor analysis is used to explain the agglomeration characteristics of respondents' activity space in each subdistrict. A total of 16 location quotients of an individual's activity time, which are mentioned above, are taken as single factors, and 57 subdistricts are taken as the research scope to construct a 57×16 data matrix. A suitability analysis test of 16 factors is carried out. The KMO value is 0.544, and the concomitant probability given by the Bartlett sphericity test is 0.000, indicating that the variables are suitable for factor analysis. Following a rule of thumb that only eigenvalues greater than 1 are important, seven factors are retained, which explains 76.26% of the total variance. To interpret and label different components, the varimax rotation technique is used to maximize the loading of a variable on one factor and minimize the loadings on all others. The variance-maximized orthogonal rotation of the initial factor load matrix converges after seven iterations. Table 5 presents the name and the loadings of these seven main factors, and Figure 2 shows the spatial distribution of scores of the main factors.

Table 5. The names and loadings of the main factors.

Main Factor Name	The Variables	Factor Load						
F1: Mixed leisure and low-income other activities	9. LQ of weekday-leisure-activities of the low-income group	**0.865**	0.006	−0.013	−0.126	0.242	0.093	0.016
	10. LQ of weekday-leisure-activities of the non-low-income group	**0.863**	0.155	−0.004	−0.147	0.116	−0.03	−0.009
	13. LQ of weekday-other-activities of the low-income group	**0.588**	0.085	0.275	0.183	−0.001	0.554	−0.067
F2: Mixed shopping activities	8. LQ of weekend- shopping -activities of the non-low-income group	0.032	**0.789**	0.261	−0.067	0.080	0.225	0.016
	7. LQ of weekend- shopping -activities of the low-income group	−0.036	**0.745**	−0.181	0.135	−0.06	0.003	0.034
	6. LQ of weekday- shopping -activities of the non-low-income group	0.277	**0.681**	0.08	−0.163	0.372	−0.052	−0.053
	14. LQ of weekday-other-activities of the non-low-income group	0.327	**0.442**	−0.097	0.217	−0.195	−0.329	0.437
F3: Low-income working activities	3. LQ of weekend-working-activities of the low-income group	−0.013	0.074	**0.877**	0.061	−0.076	0.03	−0.133
	1. LQ of weekday-working-activities of the low-income group	0.043	−0.032	**0.875**	0.058	−0.022	−0.111	0.15
F4: Non-low-income working and leisure activities	4. LQ of weekend-working-activities of the non-low-income group	0.075	0.007	−0.019	**0.896**	−0.1	−0.014	−0.112
	2. LQ of weekday-working-activities of the non-low-income group	−0.294	−0.014	0.297	**0.604**	0.002	0.11	−0.049
	12. LQ of weekend-leisure-activities of the non-low-income group	0.348	−0.039	0.071	**−0.513**	−0.27	−0.068	−0.489

Table 5. *Cont.*

Main Factor Name	The Variables	Factor Load						
F5: Low-income shopping and leisure activities	5. LQ of weekday-shopping-activities of the low-income group	0.110	0.292	−0.034	−0.097	**0.821**	−0.025	−0.066
	11. LQ of weekend-leisure-activities of the low-income group	0.370	−0.271	−0.147	0.115	**0.673**	−0.089	0.022
F6: Low-income other activities	15. LQ of weekend-other-activities of the low-income group	0.014	0.100	−0.156	0.038	−0.079	**0.876**	0.197
F7: Non-low-income other activities	16. LQ of weekend-other-activities of the non-low-income group	0.027	−0.012	0.045	−0.179	−0.076	0.173	**0.857**

Factor 1: Mixed leisure and low-income other activities. This factor accounted for 15.93% of the total variance and included three variables. The areas with higher scores of F1 are mainly the subdistricts where the surveyed community is located, indicating that the space near the community is most important for both income groups to carry out their leisure activities.

Factor 2: Mixed shopping activities. This factor accounted for 12.79% of the total variance and included four variables. The higher score areas are generally distributed evenly in the whole urban space. This may be related to the wide distribution of commercial facilities in space and the diversification of individual shopping activities, on average.

Factor 3: Low-income working activities. This factor accounted for 11.70% of the total variance and included two variables. The areas with high scores are scattered and fan-shaped, especially concentrated in the urban center and near the surveyed community, including traditional business districts in the inner city (i.e., 46_XJK, 34_HWL), emerging business districts in the inner city (i.e., 52_HS, 20_SZ, 3_JD) and suburban areas (i.e., 15_ML, 17_DS, 18_QL, 41_XL) densely gathering universities and enterprises.

Factor 4: Non-low-income working and leisure activities. This factor accounted for 10.39% of the total variance and included three variables. The areas with higher scores are mainly in the north of the main city center and southwest of the outer suburb, where many scientific, technological and cultural entrepreneurship industries are located.

Factor 5: Low-income shopping and leisure activities. This factor accounted for 9.29% of the total variance and included two variables. The F5 scores are more evenly distributed in urban spaces, and the areas with higher scores are scattered in the east and south of the inner city, the southern inner suburb and the southeast outer suburb.

Factor 6: Low-income other activities. This factor accounted for 8.21% of the total variance and included one variable. The areas with higher scores are mainly in the inner city center and the northern inner suburb.

Factor 7: Non-low-income other activities This factor accounted for 7.95% of the total variance and included one variable. The areas with higher scores are spatially dispersed, some in the urban city center and some in the northern and southwestern suburbs, indicating the diversity of the spatial distribution of other out-of-home activities of the non-low-income respondents.

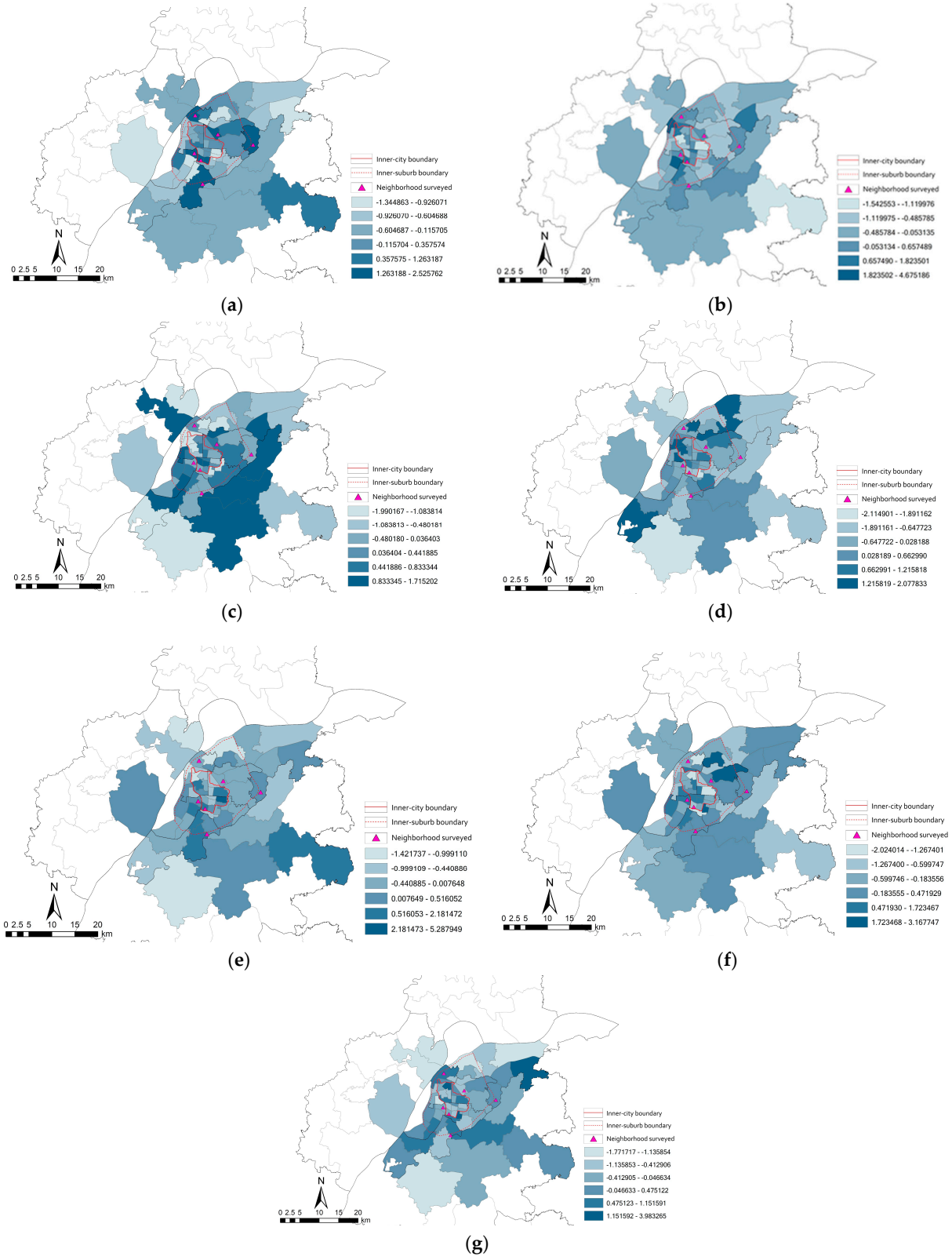


Figure 2. Spatial distribution of scores of seven main factors. (**a**) F1: Mixed leisure and low-income-other activities; (**b**) F2: Mixed shopping activities; (**c**) F3: Low-income-working activities; (**d**) F4: Non-low-income-working and leisure activities; (**e**) F5: Low-income shopping and leisure activities; (**f**) F6: Low-income other activities; (**g**) F7: Non-low-income other activities.

Based on the results of factor analysis, the systematic clustering method was adopted to identify different social areas of activity space of low- and non-low-income groups. First, Ward's method was performed to calculate the Euclidean squared distance between classes, and then the study area was classified according to the dendrogram and the actual situation. The names of the different social areas were determined by calculating the mean, square and mean of the scores for each principal factor. Finally, based on the spatiotemporal behavior survey data of low-income groups in Nanjing in 2017, the distribution of daily activities of low-income and non-low-income respondents in urban space could be divided into six types of social areas shown in Figure 3, the details of which are shown in Table 6.

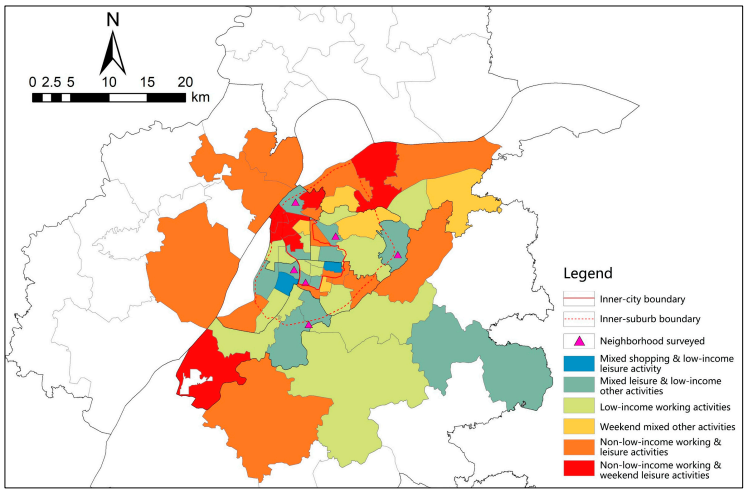


Figure 3. Spatial distribution of activity spaces of different income groups in Nanjing.

Table 6. Details of the social areas by activity time distribution of different income groups.

Social Area	Distribution	Name of Observations	Number of Observations
Cluster 1: Mixed shopping and low-income leisure activity	In central city areas with high-density residential and low-end commercial facilities	21_NY, 35_RJL	2
Cluster 2: Mixed leisure and low-income other activities	Mostly located in the subdistrict where the community is located, with a few in the southeast of the outer suburb	13_BTQ,16_CH, 30_FZM, 2_HQL, 39_MQ, 47_MYXC, 22_MCH, 31_ST, 50_SJC, 55_TXQ, 23_XL, 56_YH	12
Cluster 3: Low-income working activities	Mainly concentrated in the center of the inner-city (CBD), some are scattered in the inner-suburb area and near the surveyed community in the outer suburb	38_CTG, 17_DS, 1_FH, 28_HH,52_HS, 34_HWL, 5_HNL, 3_JD, 15_ML, 57_SHQ, 20_SZ, 37_WLC, 54_XSQ, 41_XL, 48_XLW, 46_XJK	16
Cluster 4: Weekend mixed other activities	Mainly scattered located near the surveyed communities and few on suburban fringe	40_MGQ, 29_QH, 42_XG, 51_XWH, 7_ZYM	5
Cluster 5: Non-low-income working & leisure activities	Scattered in the north and southeast of the central city, as well as the west, east and south of the suburb with clusters of science and technology industrial parks.	33_DGL,14_GL,32_GHL,24_JP,45_QX, 18_QL,19_SZ, 25_TS,10_XS,49_XWM, 26_YJ,43_YZJ,36_YYH,27_ZHM	14
Cluster 6: Non-low-income group working and rest day leisure activities	Mainly in the northwest of the central city, few scattered in the north and south suburban area.	53_BQ,9_JNL,12_MFS, 4_NHL, 6_RHNL, 44_YH, 8_YJM,11_YJL	8

In general, the spatial distribution of daily activities among different income groups is obviously different from the perspective of time allocation. Low-income participants are highly dependent on the inner city center and the inner city for their working activities. However, the work activities of non-low-income groups are more diversified and scattered, not only in the inner-city and inner-suburb areas but also in the southern, northeastern and northwestern spaces of the outer suburbs. In terms of leisure activities, low-income participants' recreational activities are highly concentrated in the surrounding spaces of the communities both on weekdays and weekends. However, the distribution of leisure activities on weekends for non-low-income groups is more diverse, while they tend to distribute their recreational activities not only in the northwest of the inner city but also in the north and south of the outer suburbs. In conclusion, the daily activities of different income groups have obvious sociospatial differentiation. It is worth noting that the urban spaces where the communities are located are important areas for the two income groups to carry out their shopping, leisure and other daily activities. This indicates that the space near home is an important area to promote the daily communication and social equity of different income groups.

3.3. Analysis of Factors Affecting the Spatial Distribution of Individual Activity Time

Considering that separate models of the participants in different communities can help us more fully understand how income and other variables affect people's usage of urban spaces and considering that the spatial patterns (such as land development intensity, resource distribution, and road network density) of the suburbs and the main city are quite different, we focus on how individuals allocate their activity time in the two different urban spaces. OLS regression models are employed to investigate how income and other factors affect individuals' usage of urban spaces. The time spent on different types of individual activities (work, shopping, leisure, others) allocated in different spaces (central city, outer suburb) is used as the dependent variable. The independent variables used in this analysis include participants' socioeconomic characteristics (e.g., gender, age, education, household structure, employment status and car ownership), activity characteristics (total travel time in the survey day, total work time in a surveyed day and the number of out-of-home locations visited in a surveyed day) and built environment characteristics (e.g., workplace in the inner city, the shortest network distance from the participant's home to the nearest metro station and the shortest network distance from the participant's home to the city center).

Tables 7 and 8 show the results of the regression models on weekdays and weekends, respectively. On weekdays, as Models 1 and 2 show, income is a significant variable affecting participants' use of urban space. Compared with non-low-income groups, low-income people have fewer working hours and less leisure time in the central city but more working hours in suburban areas. Note that the low-income participants are in a disadvantageous position in the utilization of the central city for working activity. In addition, people with intermediate levels of education, people living in *danwei* housing, commercial housing and rental housing, and people closer to the city center work longer hours in the central city and shorter hours in the suburbs. The larger the household size is and the farther the residents are from the city center, the less shopping they do in the city center and the more shopping they do in the suburbs. Car ownership is an important index to evaluate individual mobility. Participants who have a car reduce their central-urban personal activities but increase their time on work and other personal activities in the suburbs. A longer travel time reduces an individual's working time in the urban area but increases his/her working time in the suburban area and reduces his/her shopping, leisure and other activities in the suburban area.

Table 7. Factors affecting the spatial distribution of individual activity time on weekdays.

	Time Allocation in the Central City				Time Allocation in Outer Suburbs			
	Working	**Shopping**	**Leisure**	**Others**	**Working**	**Shopping**	**Leisure**	**Others**
Model 1								
Low-income (ref. non-low-income group)	−79.523 ***	4.248 *	−7.339	2.675	−7.276	6.016 ***	19.462 **	4.405
(Constant)	286.471 ***	11.743 ***	59.697 ***	28.414 ***	95.011 ***	7.286 ***	41.529 ***	14.271 ***
R Square	0.019	0.004	0.001	0.000	0.000	0.012	0.008	0.002
Adjusted R Square	0.018	0.002	0.000	−0.001	−0.001	0.010	0.007	0.000
Model 2								
Low-income (ref. non-low-income group)	−32.877 **	2.751	−13.005 *	−0.425	30.750 **	1.284	1.549	2.695
Gender (ref. women)	−9.445	−2.989	−1.000	1.957	6.166	−1.871	5.775	2.944
Age (ref. 30–59)								
29 or below	−2.553	−2.921	11.926	10.679	1.708	−3.896	−15.108	−2.218
60 or above	−18.470	3.427	20.358 **	−18.124 **	9.781	−5.918 **	32.584 ***	−5.998
Education (ref. middle school or below)								
Secondary school	38.849 **	1.451	−9.055	6.510	−39.133 **	−0.648	11.810	−2.800
College or university or above	−0.317	1.494	−2.772	−5.425	−1.147	−2.226	−6.131	−4.650
Housing type (ref. affordable housing)								
Danwei	62.829 ***	2.561	39.691 ***	13.759	−61.867 ***	−5.521 *	−36.360 ***	0.214
Commercial	71.184 ***	3.956	29.872 ***	6.343	−74.720 ***	−4.515	−38.421 ***	3.182
Rental	38.141 **	3.227	2.907	5.896	−39.708 **	−4.678 *	−24.531 ***	7.720
Family size	0.178	−2.406 **	−6.861 **	1.518	−2.071	0.372	−7.596 ***	3.632 **
Cars owned (ref. no car)	−69.532	−0.918	−6.844	−12.376 *	64.524 ***	0.715	14.158 *	12.294 **
Working time in the diary day	0.734 ***	−0.034	−0.124 ***	−0.036 ***	0.258 ***	−0.026 ***	−0.079 ***	−0.022 ***
Total travel time in the diary day	−0.280 **	0.024	−0.005	0.064	0.258 ***	−0.034 **	−0.178 ***	−0.058 *
Distance from home to the city center	−0.010 ***	−0.003 ***	−0.011	−0.003	0.010 ***	0.002 ***	0.011 ***	0.004 ***
(Constant)	87.146	48.771	189.779	53.912	−74.393	9.583	37.064	−17.263
R Square	0.601	0.200	0.339	0.051	0.233	0.209	0.367	0.098
Adjusted R Square	0.594	0.185	0.327	0.033	0.219	0.194	0.355	0.082

Notes: * Significant at the 0.10 level. ** Significant at the 0.05 level. *** Significant at the 0.01 level.

Table 8. Factors affecting the spatial distribution of individual activity time on weekends.

	Time Allocation in the Central City				Time Allocation in Outer Suburbs			
	Working	**Shopping**	**Leisure**	**Others**	**Working**	**Shopping**	**Leisure**	**Others**
Model 3								
Low-income (ref. non-low-income group)	3.123	−10.050 *	−23.411 **	−13.956 *	29.026 **	−3.299	12.251	−5.329
(Constant)	100.946 ***	40.757 ***	93.597 ***	56.263 ***	30.514 ***	16.671 ***	64.023 ***	28.711 ***
R-square	0.000	0.005	0.008	0.005	0.008	0.002	0.002	0.001
Adjusted R-square	−0.001	0.003	0.006	0.003	0.007	0.000	0.001	0.000
Model 4								
Low-income (ref. non-low-income group)	6.035	−2.595	−12.244	−5.113	35.552 ***	−3.313	2.187	−7.622
Gender (ref. women)	20.801	−9.379 *	0.314	3.764	0.622	−3.027	3.815	−7.622
Age (ref. 30–59)								
29 or below	10.193	−14.230 *	7.380	−22.503 **	−1.374	0.838	1.876	6.975
60 or above	15.378	−6.266	31.633 **	−39.229 ***	1.774	−4.226	30.225 **	−2.848
Education (ref. middle school or below)								
Secondary school	−5.054	6.116	−17.685	23.516 ***	−19.773	0.304	−3.278	−6.047
College or university or above	−76.679 ***	28.049 ***	11.984	41.769 ***	−37.286 **	5.855	−6.400	−4.736
Housing type (ref. affordable housing)								
Danwei	−28.373	15.630 *	60.394	23.275 **	−42.512 **	−0.826	−47.928 ***	7.748
Commercial	54.350 **	17.986 **	12.605	6.470	−53.874 ***	−3.325	−34.762 **	10.403
Rental	19.412	19.348 **	3.756	2.518	−16.117	0.339	−44.690 ***	28.461 ***
Family size	0.743	−0.685	−11.660 ***	3.510	−1.533	−1.319	−9.886 ***	5.966 **
Cars owned (ref. no car)	−50.860 ***	2.589	17.869	−13.754	28.197 *	2.222	12.010	8.975
Working time in the diary day	0.376 ***	−0.026 **	−0.025	−0.009	0.144 ***	−0.015 ***	−0.059 ***	−0.030 **
Total travel time in the diary day	−0.074	0.000	−0.129 *	−0.009	0.144	−0.009	0.015	0.037
Distance from home to the city center	−0.012 ***	−0.002 ***	−0.010 ***	−0.002 *	0.006 ***	0.004 ***	0.012 ***	0.006 ***
(Constant)	68.530	54.348	182.810	53.530	−39.292	2.289	49.714	−26.147
R Square	0.277	0.069	0.195	0.086	0.123	0.125	0.228	0.089
Adjusted R Square	0.264	0.052	0.180	0.069	0.107	0.108	0.214	0.072

Notes: * Significant at the 0.10 level. ** Significant at the 0.05 level. *** Significant at the 0.01 level.

As Models 3 and 4 show, the fit of the model on weekends is lower than that on weekdays, indicating that the use of individual urban space on weekends is more diversified due to the influence of individual preferences. On weekends, income remains a significant variable. Compared with non-low-income respondents, low-income respondents spend less time on shopping, leisure and other out-of-home activities in the main urban areas but more time working in the suburbs. Women, middle-aged people and highly educated people have more advantages in using the main urban area for various activities. Individuals who own a car reduce their work activities in the city and increase their work activities in the suburbs. Proximity to the city center increases the time spent in the city and reduces the time spent in the suburbs for almost all activities. It is worth noting that large numbers of low-income residents have moved from the main urban areas to the suburbs, which may cause a serious job–housing mismatch.

4. Conclusion and Discussion

This study examines how different income groups use different urban spaces in their daily lives from the perspective of time allocation. Based on social statistics and social area analysis, this study has three major findings.

First, the patterns of daily activities and utilization of urban space among different income groups are significant differences. Low-income participants are highly dependent on urban center areas around the CBD for working activities, while their leisure, shopping and other out-of-home personal activities are mainly concentrated near their homes. However, the activity pattern of the non-low-income group is different, which is manifested by the diversification and suburbanization of working and weekend leisure activity space.

Second, neighborhood spaces are important for both low-income and non-low-income individuals to carry out their daily leisure, shopping and other personal activities. Therefore, community space can be considered important for promoting communication between different income groups. The significance for urban management and planners is that improving the quantity and quality of community public service facilities is of great meaning for improving the quality of life of residents, especially low-income residents.

Third, the regression models show that in addition to income, other socioeconomic attributes (age, education level, etc.), activity space characteristics and built environment characteristics also affect individuals' urban space utilization. This research seeks to contribute to the existing literature on activity-space-based sociospatial differentiation by analyzing people's utilization of urban space from the perspective of time allocation, which can provide a useful reference for related research.

Time is an important resource that can measure the ways and degrees of individuals' utilization of the built environment. In recent decades, China's urban space has undergone tremendous changes. Most of its cities have gradually expanded from compact central cities to outward development. However, these cities are still monocentric in terms of the distribution of urban spatial resources, resulting in a very unbalanced distribution of urban spatial resources. On the one hand, the main city concentrates the highest-quality facilities and low-level tertiary industry employment opportunities. On the other hand, a large number of higher education areas, science and technology industrial parks, and country parks have been built in urban suburbs, providing a large number of knowledge-intensive high-tech employment opportunities and high-quality leisure opportunities for high-skilled people (generally high-income residents). Noting that low-income residents are experiencing a large-scale passive movement from the city center to the suburbs. Therefore, urban planners should pay attention to the characteristics of the individual use of urban space, improve nearby leisure and shopping facilities and increase employment opportunities, especially in low-income suburban communities.

There are some shortcomings in the data of this study. The individual daily activity data used in this study was collected by conducting a traditional questionnaire survey, rather than big data (i.e., mobile phone call data, social media check-in data, taxi trajectory data, etc.), which is popular in current research. Big data indeed are characterized by large

quantity and strong timeliness. However, most of these data lack details of socioeconomic attributes and activity characteristics (such as activity types and activity partners, etc.), mainly for the protection of personal privacy. Therefore, it is difficult to distinguish whether the individual is from the low-income group or the non-low-income group using big data alone. When it comes to traditional data, it is generally possible to obtain very detailed individual socio-economic attributes, while inevitably having the limitation of a relatively small data scale.

Therefore, the combination of big data and traditional data should be considered for empirical research to validate the results of this study in the future. For instance, at the general level, big data (for example, localized SIM card data) is used to cluster the activity patterns of residents of different types of housing. Then, typical communities are selected for questionnaire survey and GPS trajectory data collection. After that, the activity characteristics and urban space utilization characteristics of different income groups are summarized at the community level.

Author Contributions: Conceptualization, H.W. and M.H.; methodology, H.W., M.H. and M.-P.K.; software, H.W. and M.H.; validation, H.W. and M.H.; formal analysis, H.W. and M.H.; investigation, H.W., J.Q., J.Z. and B.H.; resources, M.H.; data curation, H.W. and J.Q.; writing—original draft preparation, H.W. and M.H.; writing—review and editing, M.H. and M.-P.K.; visualization, H.W. and J.Z.; supervision, M.H. and M.-P.K.; project administration, H.W. and M.H.; funding acquisition, H.W. and M.-P.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by The University Philosophy Social Science Fund of Jiangsu Province (Grant number 2021SJA0141). Mei-Po Kwan was supported by grants from the Hong Kong Research Grants Council (Research Matching Grants RMG 8601219, 8601242).

Institutional Review Board Statement: IRB approval for research on human subjects is not required in China.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Not applicable. Since the data include private information of the participants and thus the data cannot be shared.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Hägerstraand, T. What about people in regional science. *Reg. Sci. Assoc.* **1970**, *24*, 7–24. [CrossRef]
2. Feng, J.; Dijst, M.; Prillwitz, J.; Wissink, B. Travel Time and Distance in International Perspective: A Comparison between Nanjing (China) and the Randstad (The Netherlands). *Urban Stud.* **2013**, *50*, 2993–3010. [CrossRef]
3. Kim, J.; Kwan, M.P. Beyond Commuting: Ignoring Individuals' Activity-Travel Patterns May Lead to Inaccurate Assessments of Their Exposure to Traffic Congestion. *Int. J. Environ. Res. Public Health* **2018**, *16*, 89. [CrossRef] [PubMed]
4. Jang, J.; Ko, J. Factors associated with commuter satisfaction across travel time ranges. *Transp. Res. Part F Traffic Psychol. Behav.* **2019**, *66*, 393–405. [CrossRef]
5. Levinson, D.; Kumar, A. Activity, Travel, and the Allocation of Time. *J. Am. Plan. Assoc.* **1995**, *61*, 458–470. [CrossRef]
6. Weber, J.; Kwan, M.-P. Bringing Time Back In: A Study on the Influence of Travel Time Variations and Facility Opening Hours on Individual Accessibility. *Prof. Geogr.* **2002**, *54*, 226–240. [CrossRef]
7. Nie, P.; Sousa-Poza, A. Commute time and subjective well-being in urban China. *China Econ. Rev.* **2018**, *48*, 188–204. [CrossRef]
8. Gross, D.R. Time Allocation: A Tool for the Study of Cultural Behavior. *Annu. Rev. Anthropol.* **1984**, *13*, 519–558. [CrossRef]
9. Bhat, C.R.; Misra, R. Discretionary activity time allocation of individuals between in-home and out-of-home and between weekdays and weekends. *Transportation* **1999**, *26*, 193–209. [CrossRef]
10. Casas, I. Social Exclusion and the Disabled: An Accessibility Approach. *Prof. Geogr.* **2007**, *59*, 463–477. [CrossRef]
11. Wang, D.; Cao, X. Impacts of the built environment on activity-travel behavior: Are there differences between public and private housing residents in Hong Kong? *Transp. Res. Part A Policy Pract.* **2017**, *103*, 25–35. [CrossRef]
12. Costa, R.; de Valk, H.A.G. Ethnic and Socioeconomic Segregation in Belgium: A Multiscalar Approach Using Individualised Neighbourhoods. *Eur. J. Popul.* **2018**, *34*, 225–250. [CrossRef]
13. Wang, H.; Kwan, M.P.; Hu, M. Usage of Urban Space and Sociospatial Differentiation of Income Groups: A Case Study of Nanjing, China. *Tijdschr. Voor Econ. En Soc. Geogr.* **2020**, *111*, 616–633. [CrossRef]
14. Massey, D.S.; Denton, N.A. The dimensions of residential segregation. *Soc. Forces* **1988**, *67*, 281–315. [CrossRef]

15. Li, Z.; Wu, F. Tenure-based residential segregation in post-reform Chinese cities: A case study of Shanghai. *Trans. Inst. Br. Geogr.* **2008**, *33*, 404–419. [CrossRef]
16. Kwan, M.-P.; Murray, A.T.; O'Kelly, M.E.; Tiefelsdorf, M. Recent advances in accessibility research: Representation, methodology and applications. *J. Geogr. Syst.* **2003**, *5*, 129–138. [CrossRef]
17. Sheller, M.; Urry, J. The New Mobilities Paradigm. *Environ. Plan. A Econ. Space* **2006**, *38*, 207–226. [CrossRef]
18. Kwan, M.-P. Beyond Space (As We Knew It): Toward Temporally Integrated Geographies of Segregation, Health, and Accessibility. *Ann. Assoc. Am. Geogr.* **2013**, *103*, 1078–1086. [CrossRef]
19. Järv, O.; Müürisepp, K.; Ahas, R.; Derudder, B.; Witlox, F. Ethnic differences in activity spaces as a characteristic of segregation: A study based on mobile phone usage in Tallinn, Estonia. *Urban Stud.* **2014**, *52*, 2680–2698. [CrossRef]
20. Kwan, M.P. From place-based to people-based exposure measures. *Soc. Sci. Med.* **2009**, *69*, 1311–1313. [CrossRef]
21. Atkinson, R.; Flint, J. Fortress UK? Gated communities, the spatial revolt of the elites and time–space trajectories of segregation. *Hous. Stud.* **2004**, *19*, 875–892. [CrossRef]
22. Ellis, M.; Richard, W.; Virginia, P. Work Together, Live Apart? Geographies of Racial and Ethnic Segregation at Home and at Work. *Ann. Assoc. Am. Geogr.* **2004**, *94*, 620–637. [CrossRef]
23. Wang, D.; Chai, Y.; Li, F. Built environment diversities and activity–travel behaviour variations in Beijing, China. *J. Transp. Geogr.* **2011**, *19*, 1173–1186. [CrossRef]
24. Wong, D.W.; Shaw, S.L. Measuring segregation: An activity space approach. *J. Geogr. Syst.* **2011**, *13*, 127–145. [CrossRef]
25. Wang, D.; Li, F.; Chai, Y. Activity Spaces and Sociospatial Segregation in Beijing. *Urban Geogr.* **2012**, *33*, 256–277. [CrossRef]
26. Li, F.; Wang, D. Measuring urban segregation based on individuals' daily activity patterns: A multidimensional approach. *Environ. Plan. A Econ. Space* **2016**, *49*, 467–486. [CrossRef]
27. Ta, N.; Kwan, M.-P.; Lin, S.; Zhu, Q. The activity space-based segregation of migrants in suburban Shanghai. *Appl. Geogr.* **2021**, *133*, 102499. [CrossRef]
28. Kwan, M.-P. Space-Time and Integral Measures of Individual Accessibility: A Comparative Analysis Using a Point-based Framework. *Geogr. Anal.* **1998**, *30*, 191–216. [CrossRef]
29. Wang, D.; Li, F. Daily activity space and exposure: A comparative study of Hong Kong's public and private housing residents' segregation in daily life. *Cities* **2016**, *59*, 148–155. [CrossRef]
30. Krivo, L.J.; Washington, H.M.; Peterson, R.D.; Browning, C.R.; Calder, C.A.; Kwan, M.P. Social Isolation of Disadvantage and Advantage: The Reproduction of Inequality in Urban Space. *Soc. Forces* **2013**, *92*, 141–164. [CrossRef]
31. Silm, S.; Ahas, R. The temporal variation of ethnic segregation in a city: Evidence from a mobile phone use dataset. *Soc. Sci. Res.* **2014**, *47*, 30–43. [CrossRef]
32. Zhou, S.; Deng, L.; Kwan, M.-P.; Yan, R. Social and spatial differentiation of high and low income groups' out-of-home activities in Guangzhou, China. *Cities* **2015**, *45*, 81–90. [CrossRef]
33. Song, W.; Chen, P.; Xu, D. Research on the deprivation-type reconstruction of inner-city registered poverty space based on resettlement data of Nanjing. *Geogr. Res.* **2013**, *32*, 1467–1476. (In Chinese)
34. Zeng, W.; Rees, P.; Xiang, L. Do residents of Affordable Housing Communities in China suffer from relative accessibility deprivation? A case study of Nanjing. *Cities* **2019**, *90*, 141–156. [CrossRef]
35. Shevky, E.; Williams, M. *The Social Areas of Los Angeles*; University of California Press: Los Angeles, CA, USA, 1949.
36. Chen, N.; Akar, G. Effects of neighborhood types & socio-demographics on activity space. *J. Transp. Geogr.* **2016**, *54*, 112–121. [CrossRef]
37. Gu, C.; Wang, F.; Liu, G. The Structure of Social Space in Beijing in 1998: A Socialist City in Transition. *Urban Geogr.* **2005**, *26*, 167–192. [CrossRef]
38. Liu, Y.; Wu, F. Urban poverty neighbourhoods: Typology and spatial concentration under China's market transition, a case study of Nanjing. *Geoforum* **2006**, *37*, 610–626. [CrossRef]