Socioeconomic Disparities in Daily Activity Spaces: Insights from Smartphone Mobility Data on Non-Commuting Trips

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Abstract
Urban mobility significantly influences accessibility, social cohesion, and equity; however, non-commuting travel remains understudied. This study investigates the impact of income, age, and gender on non-commuting mobility in Seoul, utilizing large-scale smartphone data. We measure activity space distance and destination diversity to assess disparities in leisure-related movement in four different time periods of the day. Results show that higher-income groups travel farther and to more diverse destinations, while lower-income, middle-aged women, and older adults are more spatially constrained. Importantly, Gini coefficient analysis reveals significant intra-group disparities, indicating that individuals from the same demographic group but different neighbourhoods experience unequal access to mobility. These findings underscore the need for inclusive, place-sensitive mobility policies that address both intergroup and intragroup inequalities in daily urban life.

Keywords: Non-commuting mobility, activity space distance, destination diversity, socioeconomic disparities, Gini coefficient

1. Introduction

Contemporary cities face mounting pressures to ensure equitable access to urban life as mobility patterns evolve beyond routine commuting. Non-commuting travel, comprising over half of urban trips in developed economies (Miyauchi et al., 2021), includes leisure, social visits, caregiving, and errands, and plays a vital role in shaping individual physical well-being, social cohesion, and vitality (Sulis et al., 2018; Jin et al., 2024; Wang et al., 2024). The more a group of people travels to various parts of the city, the more opportunities they have for social exchange and interaction, which benefits both individual well-being and collective urban life (Mouratidis & Poortinga, 2020). Especially, the diversity in the pattern of mobility makes the catalytic impact for local economic vitality (Chong et al., 2020; Pentland, 2020). Economically, discretionary trips drive patronage of small businesses, accounting a significant part of retail spending in walkable neighbourhoods (Moyano et al., 2020). Physically, active travel modes during these trips contribute to meeting WHO-recommended daily exercise thresholds, reducing chronic disease risks (Sahlqvist et al., 2012). However, unequal access to mobility-enabling infrastructure may exacerbate socioeconomic disparities in these benefits. Cities must address inequalities in accessing vibrant areas for different socioeconomic groups, as disparities can impact physical activity and social interaction (Zhang & Warner, 2023). Barriers like safety concerns, lack of transportation, and inadequate amenities in lower-income areas often limit access for women, the elderly, and other vulnerable groups (Gauvin et al., 2020; Shoval et al., 2010).

Yet, despite its growing significance, non-commuting mobility remains underexplored in urban research. Unlike commuting, which is often fixed and purpose-driven, non-commuting mobility reflects deeper layers of spatial preference, lifestyle, and access to opportunity (Mouratidis & Poortinga, 2020; Nilforoshan et al., 2023). Disparities in such mobility, driven by income, age, gender, and neighbourhood infrastructure, can limit physical activity, social interaction, and access to vibrant areas, particularly for vulnerable groups such as women and the elderly (Shoval et al., 2010; Gauvin et al., 2020). Understanding how diverse populations navigate cities beyond the workplace is crucial for addressing spatial inequality and designing inclusive urban policies, particularly in highly stratified contexts such as Seoul (Han, 2022; Jin et al., 2024).

The primary objective of this study is to investigate how income, gender, and age influence non-commuting mobility patterns in Seoul, with a particular focus on both inter-group and intra-group disparities in access to urban spaces. Using large-scale smartphone mobility data, the study quantifies differences in activity space distance and destination diversity across four distinct time periods of the day: morning, daytime, evening, and nighttime. By applying entropy measures and Gini coefficients, it captures both spatial and temporal variation in non-commuting travel behaviour across demographic and socioeconomic lines. Through this approach, the research aims to uncover structural inequalities in daily mobility beyond work-related travel, informing the development of inclusive, time-sensitive urban policies that support equitable access to leisure, caregiving, and social opportunities for diverse population groups.

2. Literature Review

Urban mobility contributes significantly to urban sustainability by fostering social cohesion, stimulating economic activity, and reducing segregation (Xu et al., 2018; Bettencourt, 2013; Barbosa et al., 2021). It enables encounters among diverse social groups, breaks down barriers, and supports local economies by facilitating movement across neighborhoods (Chong et al., 2020; Pentland, 2020). As Jacobs (1961) noted, such everyday interactions in public spaces build community and contribute to a more inclusive urban fabric.

Mobility also plays a crucial role in mitigating urban segregation. Studies show that the places people visit for daily activities are often more socially diverse than their residential neighbourhoods (Jones & Pebley, 2014; Pinchak et al., 2021). This exposure to diversity through movement, particularly non-commuting travel, can help offset spatial isolation at home (Boterman & Musterd, 2016; Wang & Li, 2016; Lin & Ta, 2023). For example, Silm et al. (2018) found, using mobile phone data, that activity spaces beyond home and work locations tend to show lower levels of segregation. These findings highlight how everyday mobility fosters social interaction across groups.
Patterns of mobility-based segregation reveal how social divides are mirrored in travel behaviour. In U.S. cities, studies have shown significant racial segregation in mobility patterns (Hilman et al., 2022). Likewise, in Colombian cities, Lotero et al. (2016) found that individuals largely frequented places associated with their own socioeconomic class, indicating a high level of stratification. Dong et al. (2017) further demonstrated how segregation in mobility can reinforce social boundaries rather than build bridges. While South Korea is more ethnically homogeneous, it faces distinct mobility challenges, particularly disparities related to gender, age, and income, which influence who can access which parts of the city.

Built environment research frequently emphasises transport networks as mechanisms for fostering interaction across social groups (Netto et al., 2015; Carpio-Pinedo, 2021). Network centrality analyses, particularly within space syntax, are commonly used to identify highly accessible areas via walking, driving, or public transit (Rokem & Vaughan, 2018; Yunitsyna & Shtepani, 2023). These approaches assess network segregation by mapping the potential for social encounters based on spatial configuration. Expanding on this, Carpio-Pinedo (2021) introduced the concept of multi-accessibility, which captures how multimodal transport infrastructures enhance access and opportunities for social mixing. However, while these methods reveal structural potential, they do not account for actual travel behaviour, which may be constrained by socioeconomic factors, highlighting the need for empirical mobility data.

Recent mobility studies have adopted a dynamic approach to socio-spatial disparities through the concept of activity space, which captures individuals' actual travel behaviours and daily destinations (Barbosa et al., 2021; Gao et al., 2022). This perspective enables a more accurate analysis of segregation by focusing on actual patterns of urban engagement beyond the home and workplace. The increasing availability of large-scale mobility datasets, often linked with demographic attributes, enables researchers to assess how activity spaces differ across social groups. Compared to static network analyses, these data-driven methods offer more nuanced and empirical insights into how mobility behaviours shape access, inclusion, and exclusion in cities.

Several established methods exist to quantify activity space patterns, each capturing different dimensions of mobility behaviour (Barbosa et al., 2021; Yan et al., 2011). These include the gyration radius, which measures how far an individual typically moves from their centre of activity and reflects the spatial spread of movement (González et al., 2008; Yan et al., 2011); the mean activity space distance, which assesses the average travel distance or time, indicating how constrained or expansive one's daily mobility is (Barbosa et al., 2021); and destination diversity, which captures the variety of unique locations visited, often measured through entropy. Higher entropy values reflect broader engagement with the urban environment. Together, these indicators provide a comprehensive view of the magnitude and richness of mobility, enabling the identification of spatial inequalities across demographic and socioeconomic groups. While gyration radius and travel frequency require individual-level trajectory data, activity space distance and destination diversity can be derived from aggregated mobility datasets, making them especially valuable for large-scale spatial equity analysis, such as in this study.

Although age, gender, and income are widely recognised as key determinants of mobility (Panahi et al., 2023), much of the existing research tends to generalise their effects. Many studies focus on demand-side factors, such as transport infrastructure and network connectivity (Seyedrezaei et al., 2023), with limited attention to the actual mobility behaviours of vulnerable groups. Metrics such as activity space size, destination diversity, and temporal variation are essential for diagnosing spatial disparities, yet remain underutilized, particularly in studies relying on small-scale surveys. While large-scale datasets such as GPS and mobile phone records offer more objective and granular insights, their potential for revealing urban mobility inequalities has not been fully realised.

Despite growing theoretical discussions on gendered urban spaces in Korea (Ahn, 2011), empirical research on gendered mobility patterns in Seoul remains limited. This gap is particularly significant given the city's dense, transit-oriented urban form and the critical role that gender plays in shaping access to urban opportunities. At the same time, Korea's rapidly ageing population presents distinct mobility challenges, as older adults often exhibit different travel behaviours due to physical, cognitive, or social constraints (Giménez-Nadal et al., 2024; Arentze et al., 2008). Mobility disparities linked to income also persist, with lower-income individuals facing obstacles such as limited transport options and reduced access to diverse destinations (Yabe et al., 2023). Understanding how gender, age, and income intersect to shape urban mobility is crucial for designing equitable cities. This is particularly urgent in metropolitan areas like Seoul, where, contrary to expectations, residents often experience lower exposure to socioeconomically diverse populations, suggesting that spatial segregation may be more pronounced in cosmopolitan settings than assumed (Nilforoshan et al., 2023).

Socioeconomic factors play a pivotal role in shaping how individuals navigate and utilise urban spaces (Gauvin et al., 2020; Giménez-Nadal et al., 2024; Jo et al., 2020). Variables such as income, education level, and occupation influence where people live, work, and participate in leisure activities (Macedo et al., 2022; Salon & Gulyani, 2010). These characteristics are closely linked to mobility patterns, which reflect a city's broader social and economic structure (Chong et al., 2020). For example, lower-income individuals may lack access to private transportation and rely more heavily on public transit, which limits their spatial reach and activity spaces. Analysing these socioeconomic dimensions helps identify the root causes of spatial inequity and informs the development of targeted policy interventions.

Socioeconomic disparities in mobility have critical implications for inclusive urban planning. Mobility data can guide policies that ensure all residents, regardless of income, age, or gender, have equitable access to services, jobs, and leisure opportunities. By addressing spatial inequalities and anticipating the needs of ageing populations and gender-specific mobility patterns, cities can become more resilient, adaptive, and socially cohesive. In Korean cities especially, demographic trends point to a growing challenge: without proactive planning, elderly residents and women may face increasing constraints in accessing activity spaces (Kim & Kim, 2020). To address these issues, this study employs data-driven methods to investigate spatial and temporal disparities in non-commuting mobility across Seoul.
By focusing on the diverse array of activities beyond the traditional commute, our study contributes to a more nuanced understanding of urban mobility. This perspective is essential for developing more liveable, inclusive, and efficient urban environments, enabling urban planners and policymakers to better address the needs of various demographic groups and foster a more equitable and vibrant city.

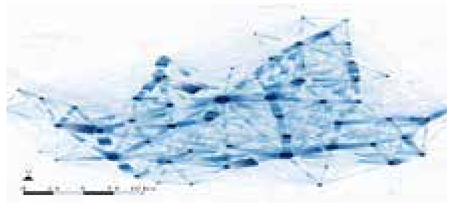
3. Methodology

3.1. Data and study area

This study focuses on the city of Seoul, South Korea, which is home to over 9 million residents and characterised by a high-density urban environment. Seoul presents a compelling case for mobility research due to its marked socioeconomic diversity, rapidly ageing population, and spatial disparities in neighbourhood income. We utilise two datasets in this study.

To analyse non-commuting mobility patterns, we employed anonymised large-scale smartphone mobility data from KT (Korea Telecom), made available through the Seoul Open Data Plaza (data.seoul.go.kr). The dataset captures origin–destination (O–D) flows between administrative neighbourhoods (dong level), disaggregated by age, gender, and purpose of travel. Mobility records are timestamped and categorised by trip type, allowing us to isolate non-commuting activities, such as leisure, caregiving, and errands (Table 1). The dataset was also crucial for analysing socioeconomic indicators and their relationship with urban mobility.

Table 1. Structure and visualization of O–D mobility data

Classification	Structure	O-D Visualization
Departure time	yyyy/mm/dd hh:mm (20-min span)	
Arrival time	yyyy/mm/dd hh:mm (20-min span)	
Departure area	Neighbourhood unit	
Arrival area	Neighbourhood unit	
Age groups	5-year-old span	
Mobility type	H – residence, W-Work and school, E- Other	
Travel time	Average travel time (minutes)	
Number of people moving	Sum of people moving	

To examine the impact of socioeconomic factors on urban mobility patterns, we used indicators related to age, gender, and income. Age and gender data were sourced from the KT Human Movement dataset, which provides mobility information segmented by 5-year age groups. In addition, we incorporate neighbourhood-level income data from the Smart Policing Big Data Platform, which aggregates mean income estimates to the same spatial units used in the mobility data. This integration allows us to examine how income intersects with age and gender in shaping daily non-commuting mobility across the city.

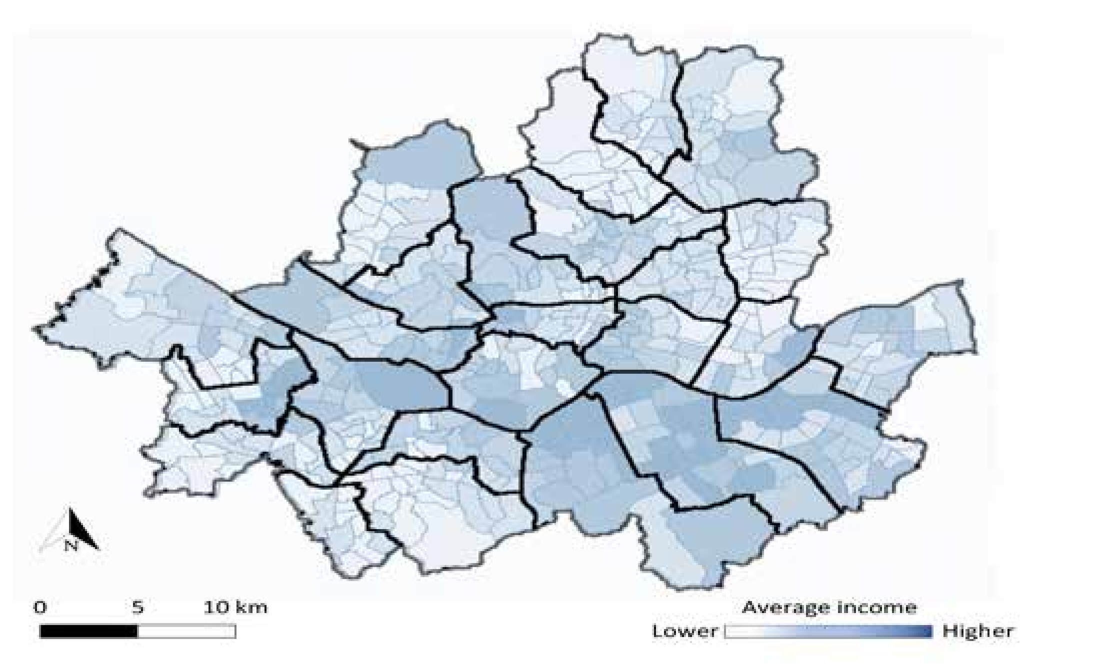


Figure 1. Average income of neighbourhoods in Seoul

3.2. Pattern extraction and processing

We began by preprocessing the origin–destination (O–D) mobility data to remove invalid records (Figure 2). Trips were limited to those within Seoul, with filters applied to exclude identical origin-destination pairs, travel times exceeding 100 minutes to remove implausible trips and outliers, and individuals under the age of 10.

Trip types were classified using purpose codes, and commuting trips (e.g. HW, WH, EH, EW) were excluded. Only non-commuting trips, including EE (other–other), HE (home–other), and WE (work–other), were retained, representing discretionary activities such as leisure, social visits, shopping, and personal errands. Records were grouped into four time periods (morning, daytime, evening, and nighttime) to enable temporal analysis.

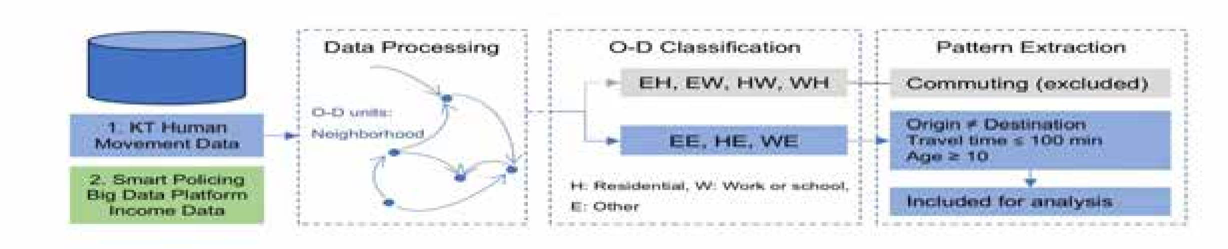


Figure 2. Data Processing and Pattern Extraction Workflow for Non-Commuting Mobility Analysis

The cleaned mobility data were then merged with neighbourhood-level income data using administrative codes. This integration produced a structured dataset disaggregated by gender, age, time of day, and income, which formed the basis for our analysis of activity space distance and destination diversity.

3.3. Mobility and inequality metrics

Figure 3. Framework for measuring and comparing socioeconomic disparities in non-commuting mobility

The empirical analysis in this study aims to explore urban mobility patterns within Seoul's neighbourhoods, with a focus on variations across different socioeconomic groups, particularly age, gender, and income. To quantify non-commuting mobility, we employed two key indicators: activity space distance and destination diversity (Figure 3). Activity space distance refers to the average travel time (minutes) from a given origin neighbourhood, weighted by the number of individuals from each socioeconomic group taking each trip. It serves as a proxy for the spatial reach of daily movement. Higher values reflect a broader reach of urban activities, implying that individuals are willing or able to travel longer durations to access diverse areas of the city, while lower values may indicate spatial constraints or reliance on nearby amenities.

To calculate activity space distance, we used the following formula to determine the average travel time for an individual's or group's trips:

$$Activity\ space\ distance = \frac{1}{N}\sum_{i=1}^{N} t_i$$

N is the total number of trips made by within a group during the specified time period,
t_i represents the travel time (in minutes) for each trip from the origin to the destination.

To calculate destination diversity, we used Shannon entropy based following formula:

$$Destination\ diversity = -\sum_{i} p_i \log_2(p_i)$$

where;
p_i is the proportion of visits to destination i relative to the total number of visits across all destinations for a person or group.

Next, destination diversity is measured using Shannon entropy (log scale), which captures the variety and evenness of destination choices. Entropy values increase with the number and distribution of unique destinations, providing insight into how dynamic or concentrated a socioeconomic group's urban engagement is. A higher entropy value indicates that a person visits a wider range of destinations, suggesting a more varied and dynamic urban experience. In this study, entropy was calculated for each gender–age group and income level, across four daily time periods. Using graphical visualizations, first, we showed intergroup mobility comparison between different socio-economic groups.

Secondly, to assess intra-group inequality in mobility access within the same socioeconomic groups, we computed the Gini coefficient for both indicators across neighbourhoods. This metric reveals how equally activity space distance or destination diversity is distributed within demographic groups. A higher Gini suggests greater internal disparity, some individuals in the group are more mobile or spatially privileged than others. This approach allows us to capture not just average behaviour, but also equity of mobility access within each group. The formula for Gini coefficient is as follows:

$$G = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\left|x_i - x_j\right|}{2n^2\bar{x}}$$

Where x_i and x_j represent values of the mobility indicator for each neighbourhood, is the number of observations, and x is the mean value of the indicator.

Thirdly, we examined temporal variation in mobility by dividing the day into four distinct periods: morning (06:00–08:59), daytime (09:00–15:59), evening (16:00–18:59), and nighttime (19:00–23:59). This segmentation captures fluctuations in mobility behaviour across the daily cycle, allowing us to observe how different demographic groups engage with the city at various times. For example, working-age adults may be more active during rush hours, while older adults may concentrate their trips in midday periods. This temporal lens was applied not only in the graphical inter-group analysis, but also in the intra-group inequality assessment, enabling us to investigate whether mobility disparities persist or vary by time of day.

Together, these metrics support a multidimensional understanding of urban mobility: activity space distance reflects the scale of movement, entropy captures spatial diversity, and the Gini coefficient uncovers hidden inequalities in access. This framework enables us to examine how age, gender, and income shape not only who moves, but also how equitably urban opportunities are distributed among similar individuals

4. Results

This section presents the main findings on non-commuting mobility. Results are organised into two parts: inter-group differences across age, gender, and income groups, and intra-group disparities within the same socio-economic groups at the neighbourhood level. We first report patterns in activity space distance and destination diversity, followed by an assessment of inequality using the Gini coefficient.

4.1. Inter-group differences in mobility

In this investigation, we focused on urban mobility, examining activity space distance and destination diversity, to understand demographic differences in urban movement patterns across Seoul.

4.1.1 Activity space distance

Figure 4 and Figure 5 illustrate gender and age differences in activity space distance across four daily time periods. These periods, morning, daytime, evening, and nighttime, were defined to reflect typical daily rhythms in urban life, capturing commuting hours, discretionary travel, and evening activities. This temporal segmentation enables a more nuanced understanding of how mobility patterns shift across the day. While some trends remain consistent, such as the reduced mobility of older adults and children under 15, other patterns, particularly gender gaps among younger groups, vary considerably depending on the time of day.

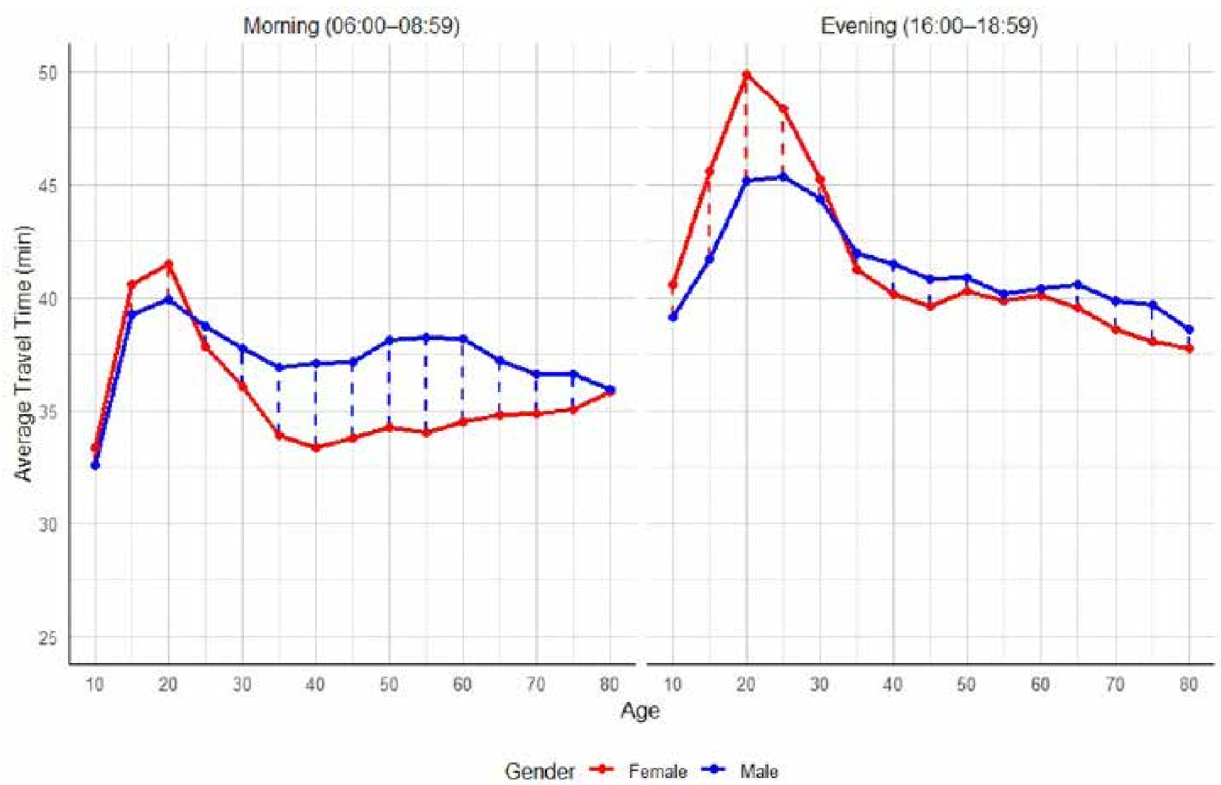


Figure 4. Gender and age differences in average travel time across morning and evening.

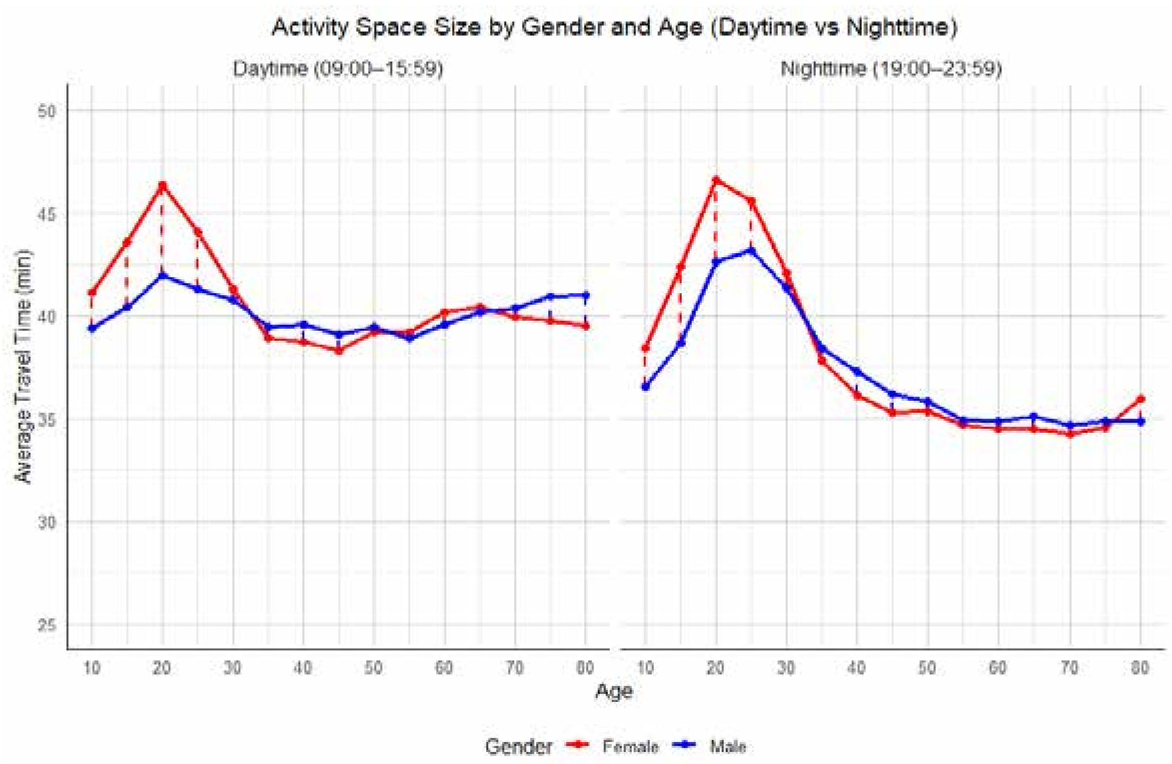


Figure 5. Gender and age differences in average travel time across daytime and nighttime

During the morning period, activity space distance is relatively short compared to the other three periods, suggesting more spatially constrained leisure or caregiving activities in the early hours. As the day progresses, travel distances increase, peaking during the daytime and remaining relatively high into the evening, before declining slightly at night. When disaggregated by gender and age, individuals in their 20s and 30s consistently exhibit the greatest spatial reach, while children under 15 and older adults maintain shorter travel ranges across all periods. The generational mobility gap is most pronounced during the evening and nighttime.

Gender differences are most notable in the morning, where men over the age of 25 tend to travel farther than women in the same age group. In other time periods, this gender gap among adults narrows. However, across the daytime, evening, and nighttime, young women under the age of 25 consistently travel farther than young men, likely reflecting their engagement in discretionary activities such as shopping or social visits. This trend stabilises after age 30, where gender differences become minimal.

Next, we examined how neighbourhood income influences travel distance across daily periods (Figure 6 & Figure 7). The results reveal a clear negative association between income and activity space distance during the morning (06:00–08:59), where residents of lower-income neighbourhoods tend to travel farther than those from higher-income areas. This trend is supported by a moderate R^2 value of 0.31, indicating a meaningful level of explanatory power. The pattern may reflect unequal distribution of leisure or essential amenities, forcing residents in less affluent areas to travel farther during early hours to reach services located in wealthier parts of the city.
During the daytime, however, the relationship between income and travel distance almost disappears (R^2 = 0.008), suggesting a more level playing field for mid-day mobility regardless of income. In the evening and nighttime, the association reverses slightly, particularly in the evening (R^2 = 0.119), with higher-income residents exhibiting longer average travel distances. This shift could be attributed to lifestyle-related discretionary activities, such as dining or cultural outings, which are more accessible to wealthier populations. These findings demonstrate how mobility inequality fluctuates throughout the day, with structural limitations more pronounced in the morning and lifestyle-based divergence emerging later in the day.

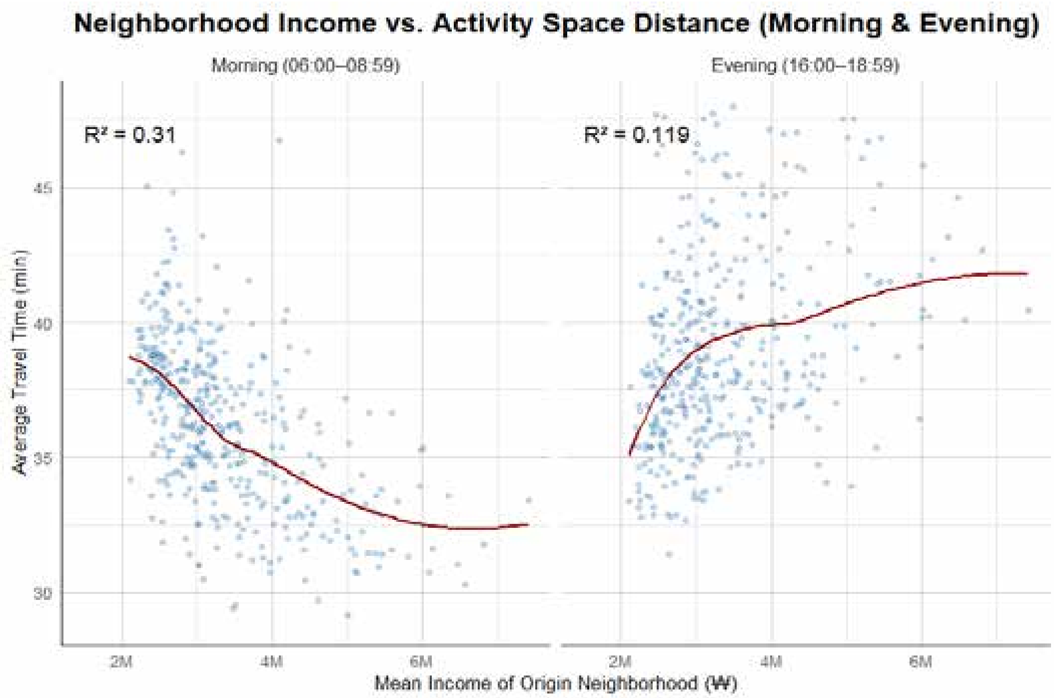


Figure 6. Neighbourhood income levels and average travel time across morning and evening

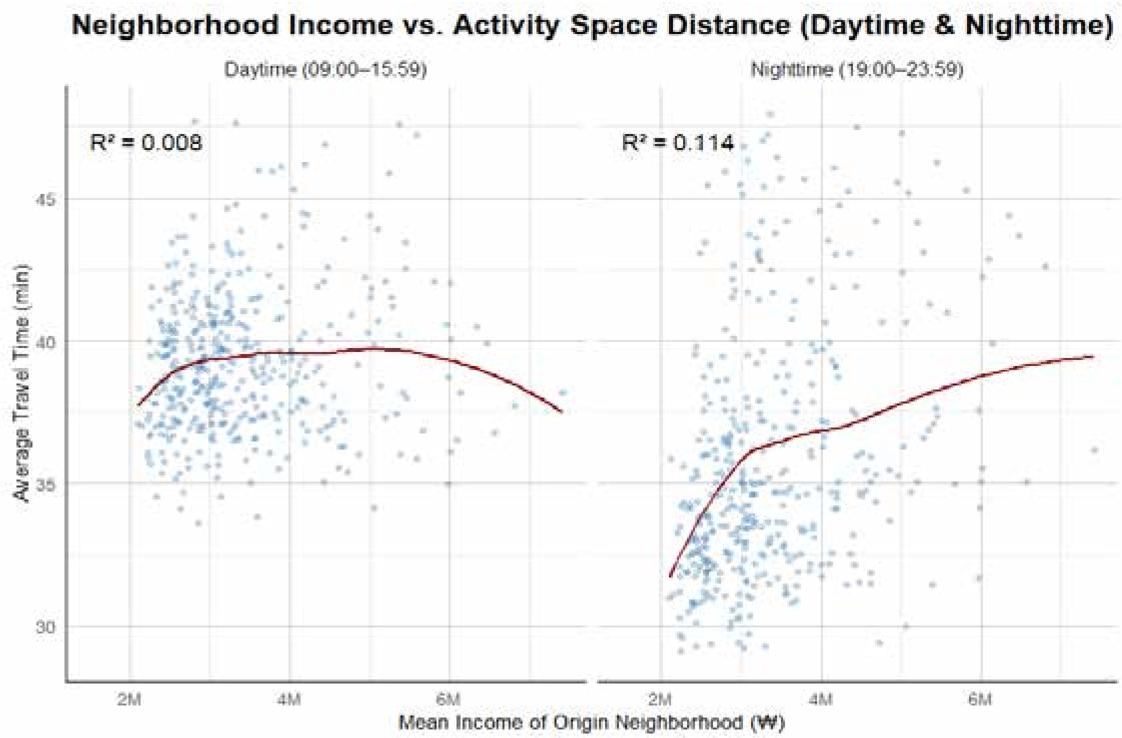


Figure 7. Neighbourhood income levels and average travel time across daytime and nighttime

While the income-travel time correlation is relatively weak, these observations provide valuable insights for transportation planning, as income-level disparities impact accessibility and the spatial distribution of activity spaces across the city.

4.1.2 Destination diversity

Our second investigation of inter-group mobility differences, destination diversity, is measured using Shannon entropy. It captures the extent to which individuals or groups visit a wide range of neighbourhoods during non-commuting trips. Unlike activity space distance, which measures the scale of travel, entropy captures the variety and distribution of destinations, reflecting the breadth of urban engagement. Higher values indicate more diverse mobility patterns and potentially greater access to urban opportunities, while lower values suggest spatial confinement or routine-based travel. Entropy is particularly useful for identifying subtle mobility inequalities, where long distances may mask limited exposure to different areas.

Figure 8 and Figure 9 Illustrate gender and age differences in destination diversity across four daily time periods. Patterns of destination diversity show distinct trajectories for men and women. Notably, children under 15 and elderly individuals over 60 exhibit generally lower destination diversity across both genders, suggesting that these groups tend to frequent a smaller, more consistent set of locations in their daily non-commuting activities. However, the gap between the two genders is small in both the early and later stages of life.

For women, entropy peaks in the 20–25 age group across all time periods and declines steadily with age, suggesting that younger women are more likely to engage with a broader set of destinations, possibly linked to lifestyle, education, or social activities. After age 25, their spatial diversity gradually narrows, reflecting more routine-based mobility or caregiving responsibilities. In contrast, men exhibit a more sustained level of high entropy between the ages of 25 and 60, particularly during the morning and daytime, with a peak around age 45 in the morning period. This implies that adult males maintain a broader range of destination choices throughout middle adulthood. However, during nighttime, men’s entropy declines more rapidly after age 30, mirroring the trend observed in women. These gendered patterns highlight how mobility diversity is shaped not only by age but also by differing social roles and temporal rhythms across the day.

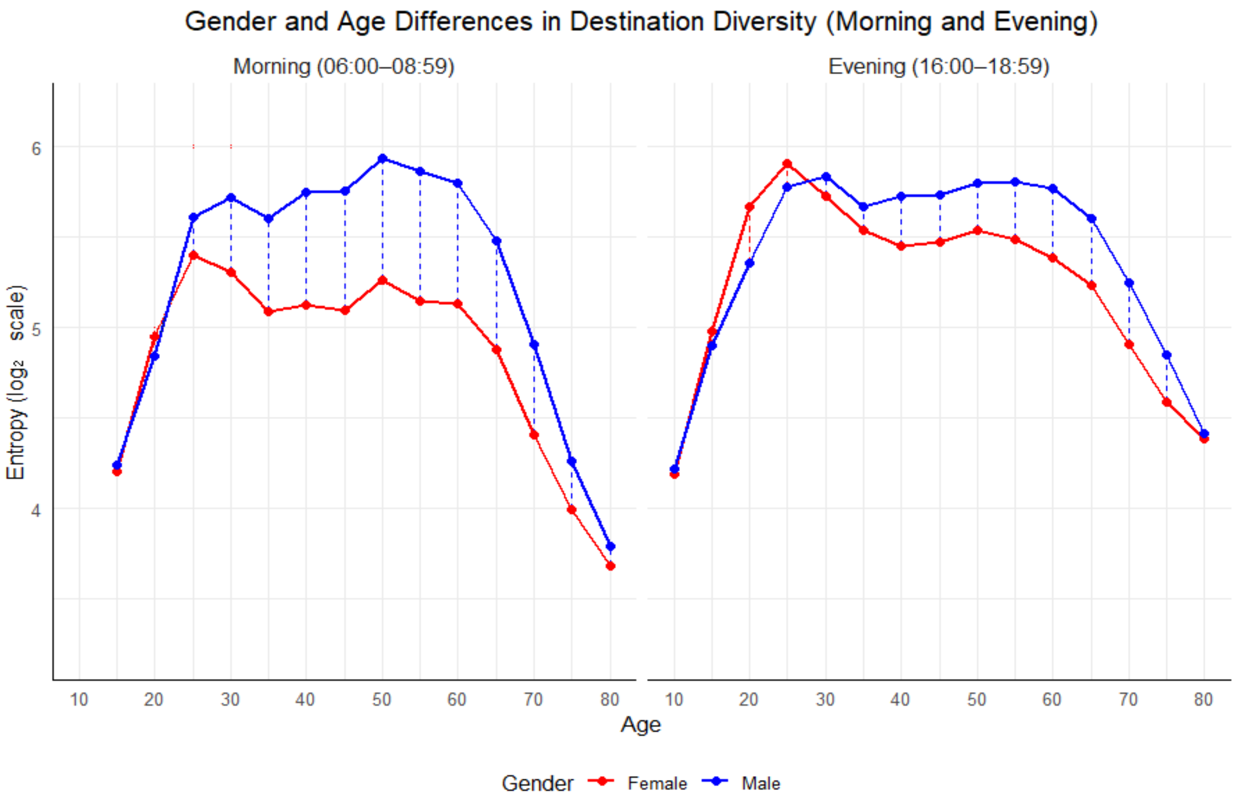


Figure 8. Gender and age differences in destination diversity across morning and evening.

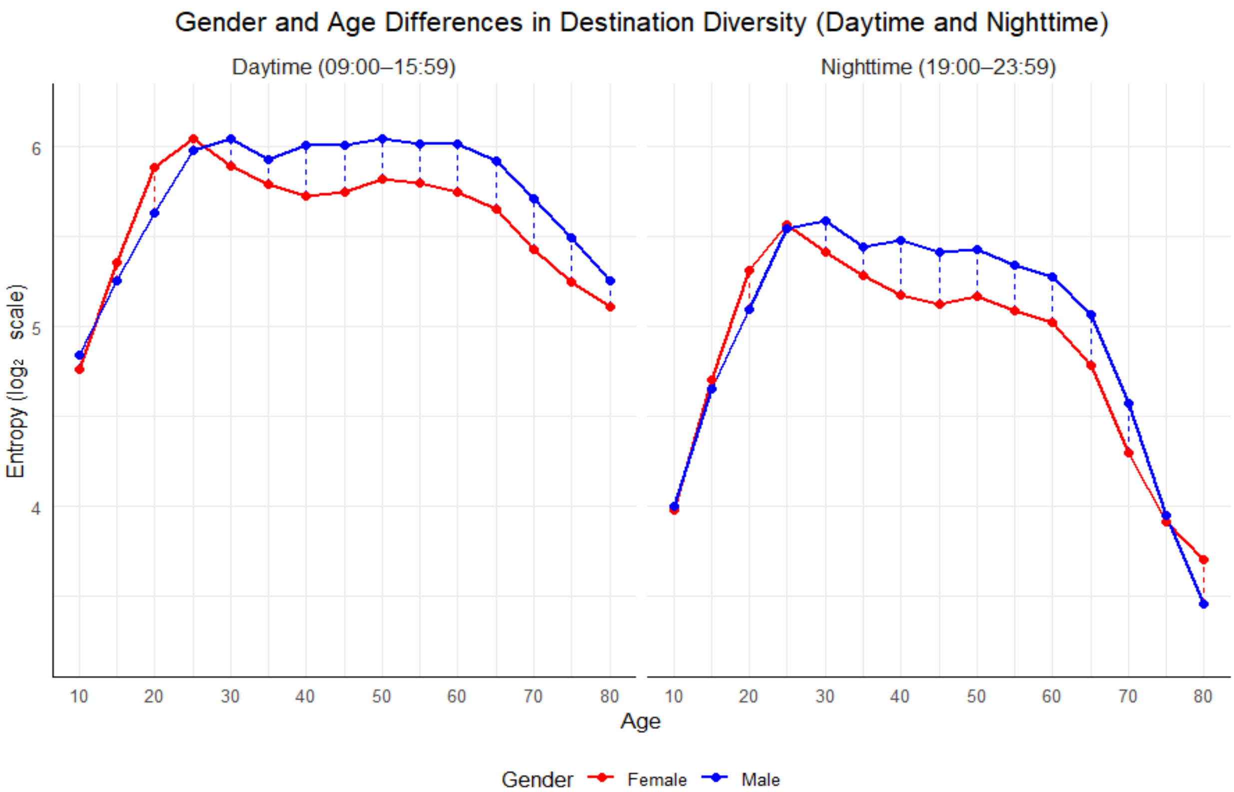


Figure 9. Gender and age differences in destination diversity across daytime and nighttime

Next, we examined how neighbourhood income levels influence destination diversity across four daily time periods (Figure 10 & Figure 11). The analysis reveals a distinctive temporal pattern. In the morning period (06:00–08:59), individuals from higher-income neighbourhoods display lower entropy, indicating more routine-based or spatially confined travel. Higher-income residents might be more likely to engage in early morning activities that are routine and closer to home, such as visiting local parks or cafes, which are less diverse in nature compared to activities later in the day. This contrasts with the rest of the day, when entropy increases with income, suggesting that wealthier individuals engage with a broader variety of urban destinations. This shift reflects the greater flexibility and resources that higher-income groups have to access a diverse range of activities across the city. These results highlight how spatial inequality unfolds throughout the day. While high-income residents initially show lower diversity in the morning, their access to varied destinations expands in later periods. In contrast, lower-income groups consistently exhibit more limited spatial diversity, suggesting constraints in reaching a broad range of urban amenities. This persistent disparity may reduce opportunities for social interaction and urban participation, highlighting the need for policy efforts that enhance access to diverse destinations in underserved areas. The observed differences in destination diversity highlight the need for targeted urban planning interventions to address the specific mobility needs and constraints of different demographic groups, promoting more equitable access to urban resources and opportunities. This intervention not only promotes social equity but also enhances the overall vibrancy and sustainability of urban communities.

Figure 10. Income factor in destination diversity across morning and evening

Figure 11. Income factor in destination diversity across daytime and nighttime

4.2. Intra-group mobility inequality

To complement inter-group comparisons, we calculated Gini coefficients for both activity space distance and destination diversity across Seoul's neighbourhoods, segmented by age group, gender, income group, and time of day (Table 2 & Table 3). These inequality metrics provide a more profound insight into intra-group spatial disparity, revealing the varied mobility experiences within the same demographic or income bracket. While average values describe general mobility levels, the Gini coefficient highlights how unevenly mobility is distributed within groups. A higher Gini value indicates greater internal disparity, suggesting that some individuals enjoy broader spatial access while others remain more constrained. This approach allows us to uncover hidden inequalities in access to urban opportunities, even among individuals who share similar socioeconomic characteristics.

The Gini coefficients for activity space distance reveal notable intra-group disparities across both demographic and income groups (Table 2). Among age groups, younger individuals under 25 exhibit the highest inequality, particularly in the morning (Gini = 0.109 for males; 0.110 for females), suggesting that travel opportunities within this group vary widely depending on neighbourhood context. In contrast, middle-aged adults (35–60) consistently exhibit low Gini values across all time periods, indicating more uniform spatial behaviour within this group. Gender differences are minimal overall, though young women display slightly higher inequality than their male counterparts during the evening and nighttime periods.

Table 2. Intra-group inequality in activity space distance (Neighbourhood-level Gini coefficients)

Socioeconomic Factors			**Gini coefficient of Activity Space Distance (unit = neighbourhood)**			
			morning	evening	daytime	nighttime
Age / Gender	Under 25	M	0.109	0.077	0.051	0.081
		F	0.110	0.081	0.055	0.087
	25-34	M	0.074	0.065	0.047	0.081
		F	0.073	0.071	0.054	0.092
	35-60	M	0.073	0.059	0.042	0.066
		F	0.067	0.061	0.044	0.068
	60+	M	0.075	0.057	0.040	0.080
		F	0.079	0.063	0.041	0.079
Income	Low		0.083	0.060	0.046	0.072
	Lower-Middle		0.082	0.060	0.046	0.073
	Upper-Middle		0.081	0.071	0.050	0.088
	High		0.081	0.069	0.054	0.084

When examining income groups, the distance between activity spaces becomes more unequal among higher-income groups, especially during evening and nighttime hours. This may reflect greater individual variation in lifestyle flexibility and mobility choices among wealthier residents. Additionally, the spatial heterogeneity of affluent neighbourhoods may contribute to this disparity, as some high-income areas are centrally located with dense access to amenities. In contrast, others are situated in more suburban or secluded zones. This geographic variation could lead to differing levels of dependency on travel, thus widening intra-group inequality. Conversely, lower-income groups exhibit slightly more constrained but uniform mobility patterns, likely reflecting shared limitations in transportation access and discretionary travel options. Temporal differences are also evident: inequality is generally lowest during daytime, suggesting that mobility is more evenly distributed across groups in midday hours compared to mornings or evenings. The Gini coefficients for destination diversity highlight additional layers of inequality within socioeconomic groups (Table 3). Unlike activity space distance, which reflects the extent of spatial reach, entropy-based Gini values capture variation in the diversity of urban experiences. The analysis reveals that younger age groups, particularly those under 25, consistently exhibit the highest intra-group inequality across all time periods, especially during the morning and evening hours. This suggests that while some young individuals engage with a wide range of destinations, others in the same group remain limited to a narrow set of familiar locations. In contrast, older adults (60+) display more consistent and lower levels of entropy inequality, reflecting relatively uniform, though limited, mobility behaviour across this group.

Table 3. Intra-group inequality in destination diversity (Neighbourhood-level Gini coefficients)

Socioeconomic Factors			Gini coefficient of Destination Diversity (unit= neighbourhood)			
			morning	evening	daytime	nighttime
Age / Gender	Under 25	M	0.141	0.083	0.062	0.090
		F	0.154	0.092	0.070	0.099
	25-34	M	0.053	0.040	0.037	0.054
		F	0.055	0.043	0.039	0.060
	35-60	M	0.046	0.048	0.035	0.059
		F	0.051	0.053	0.037	0.066
	60+	M	0.105	0.083	0.050	0.121
		F	0.095	0.082	0.052	0.106
Income	Low		0.119	0.078	0.057	0.095
	Lower-Middle		0.112	0.077	0.053	0.094
	Upper-Middle		0.109	0.077	0.055	0.102
	High		0.099	0.075	0.051	0.096

Gender patterns are also notable: while overall differences between males and females are small, women consistently exhibit higher inequality in destination diversity compared to their male counterparts. This may reflect a divergence in lifestyle and access, where some women participate in diverse activities across the city. In contrast, others remain more spatially restricted due to social or safety concerns. As with activity space distance, the middle-aged group (35–60 years old) shows the most uniform diversity patterns across neighbourhoods.

Across income groups, the highest Gini values are observed in high-income neighbourhoods, particularly during daytime and nighttime hours. This mirrors the pattern observed in activity space distance and likely stems from the same spatial heterogeneity of affluent areas, some offering rich, central amenities and others being more peripheral. In contrast, lower-income groups exhibit more uniform but limited diversity, highlighting again the shared constraints in their activity space. These results highlight that even within high-mobility groups, inequality in access to urban variety persists, with some individuals enjoying rich urban experiences while others remain excluded.

Across income groups, differences in Gini values for destination diversity are relatively modest, but a few patterns emerge. In the morning, lower-income neighbourhoods show slightly higher inequality, suggesting that access to diverse destinations may be more uneven at the start of the day. And, in general, inequality is lower in daytime and evening for all income groups.

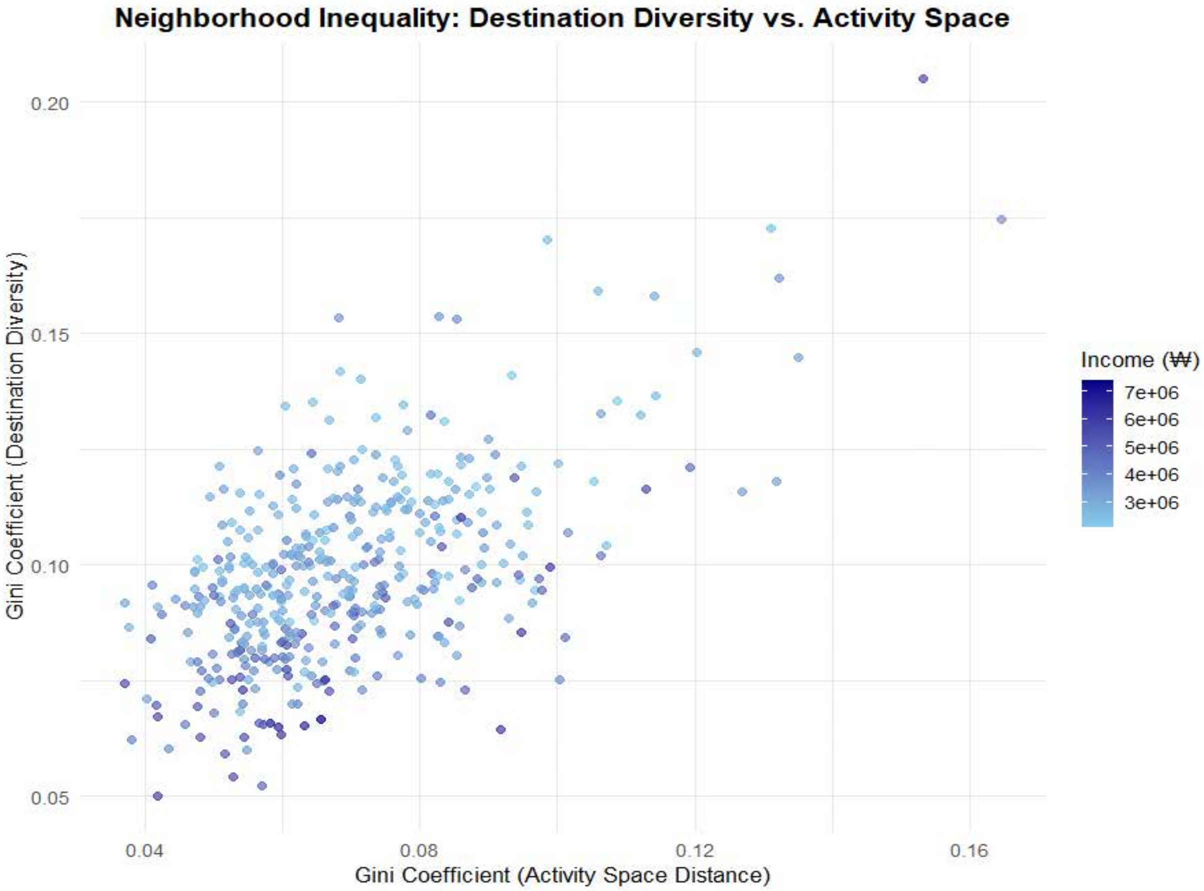


Figure 12. Relationship between intra-neighbourhood inequality in activity space distance and destination diversity. Each dot represents a Seoul neighbourhood; colour intensity reflects average neighbourhood income.

Figure 12 presents a bivariate relationship between neighbourhood-level inequality in activity space distance and destination diversity, with each dot representing a Seoul neighbourhood and coloured by average income level. The weak positive trend suggests that these two dimensions of spatial inequality are related but not strongly correlated, indicating that they capture different aspects of mobility disparity. While some neighbourhoods show low inequality in both metrics, others experience high disparity in either scale or diversity of movement. Notably, higher-income areas (darker dots) appear across a wide range of Gini values, reinforcing earlier findings that wealth does not necessarily imply internal equity. This figure underscores the importance of analysing both activity space and destination diversity to fully understand the multi-faceted nature of urban mobility inequality.

5. Discussions and Conclusions

5.1. Discussions

This study examined non-commuting mobility patterns in Seoul using large-scale smartphone data, focusing on the spatial scale and diversity of daily movement across different socioeconomic groups. We found clear inter-group disparities: higher-income individuals and those in their 20s and 30s travelled farther and engaged with a broader range of destinations. At the same time, older adults and children exhibited more spatially confined routines. Gender differences were more complex; middle-aged women tended to show reduced spatial reach, likely due to caregiving roles or safety concerns, whereas younger women displayed broader destination diversity, especially during daytime and evening hours.

In addition to group-level differences, we revealed substantial intra-group inequalities by calculating Gini coefficients for both activity space distance and destination diversity. These disparities were especially pronounced in young individuals and high-income neighbourhoods. Temporal segmentation further revealed how mobility inequalities shift throughout the day; morning periods exhibited more uniform travel patterns, while evening and nighttime hours amplified these disparities. Together, these findings highlight that urban mobility is stratified not only across but also within demographic and income groups, necessitating multidimensional and time-sensitive approaches to equity analysis.

This study provides new theoretical insights into how socioeconomic status affects both the scale and diversity of urban mobility. By employing two complementary indicators —activity space distance and destination diversity —we demonstrate that these dimensions, together, provide a nuanced understanding of spatial inclusion. Higher mobility is not just about travelling farther, but also about engaging with a broader array of destinations, each essential for capturing different facets of urban opportunity and interaction.

Our findings reinforce the value of temporal segmentation in mobility analysis. By examining morning, daytime, evening, and nighttime periods separately, we uncover dynamic patterns that would be masked in daily aggregates. Gender disparities, for instance, are not static: younger women display high diversity during the daytime and evening, while the gap narrows or reverses at other times. Similarly, older adults consistently exhibit reduced mobility diversity, suggesting age-related constraints that persist regardless of time. These findings extend earlier work (Gauvin et al., 2020; Zhou et al., 2022) by demonstrating how gender- and age-related disparities in mobility persist across different groups and vary over time. For instance, the gap between genders for both activity space distance and destination diversity of adults (30-60) is highest in the morning. This reinforces the importance of temporally sensitive planning strategies.

Our findings reveal notable variations in mobility patterns across women's life stages. Women under 30 display higher mobility diversity and longer travel distances, likely reflecting more flexible lifestyles and fewer caregiving responsibilities. However, this trend reverses after the age of 30, when mobility becomes more localised, suggesting increasing spatial constraints linked to societal expectations around work and family. On the other hand, for both genders, mobility inequality is highest among younger individuals under 25. This may reflect differing levels of family dependence or opportunity; some youth experience greater autonomy and flexibility in their daily routines. In contrast, others remain more constrained by family obligations or limited resources. These findings extend urban mobility theory by demonstrating how gendered and generational life-course transitions influence spatial behaviour, and they underscore the importance of policies that address mobility equity across different life stages.

Importantly, we argue that activity space distance and destination diversity function as proxies for access to urban social and economic life. Broader activity spaces and richer destination portfolios increase opportunities for interaction, participation, and inclusion. These mobility patterns should therefore be seen not only as behavioural outcomes but also as indicators of underlying urban equity, or lack thereof. As Jacobs (1961) argued, diverse, interconnected urban experiences are key to vibrant city life; our findings show how mobility constraints limit these opportunities for certain groups.

While our study interprets broader activity spaces and greater destination diversity as indicators of opportunity and inclusion, it is important to acknowledge that these patterns do not universally reflect enhanced access or well-being. In some cases, longer travel distances may result from a lack of proximate amenities—indicating spatial exclusion rather than mobility freedom. Conversely, shorter travel distances can signal either convenience and sustainability, or constraints imposed by social, economic, or physical barriers. This duality underscores the complexity of interpreting activity space distance. For instance, the principles of the n-minute city (Moreno et al., 2021) emphasise the benefits of proximity-based living, where diverse urban functions are accessible within a short distance, supporting convenience, equity, and environmental sustainability. From this lens, high mobility may sometimes reflect urban inefficiencies rather than voluntary engagement. While destination diversity is often a clearer indicator of social interaction and urban integration, it too must be contextualised. Future research should distinguish between proximity by choice and proximity by constraint, ideally by integrating mobility data with spatial, social, and qualitative indicators to better understand the lived experience behind observed patterns.

The findings of this study carry important implications for designing more equitable and inclusive urban policies. First, the consistent disparities observed across age, gender, and income groups suggest the need for targeted interventions to support the mobility of underrepresented populations, particularly elderly residents, lower-income individuals, and middle-aged women. Enhancing access to diverse and proximate amenities in underserved neighbourhoods can reduce spatial exclusion and promote urban sustainability. Furthermore, by promoting broader spatial engagement, as highlighted by Wang et al. (2024), infrequent, non-commuting activities can have a significant impact on economic outcomes. Second, the temporal segmentation of mobility patterns highlights that inequality fluctuates across the day, signalling an opportunity for time-sensitive policies, such as improving nighttime transit services or ensuring daytime safety for women and elderly populations. Third, planners should adopt a multidimensional framework that integrates both activity space distance and destination diversity into accessibility metrics. For instance, Zhou et al. (2022) demonstrated that elderly individuals rely heavily on public transport to access essential services. This should also be considered in relation to daily time periods. Rather than focusing solely on commute distances, future urban planning should account for the richness of everyday spatial engagement as a measure of urban inclusion. By doing so, cities can move closer to the ideals of the 15-minute city, where all residents, regardless of socioeconomic background, can access opportunities within reach, by choice rather than by constraint.

While this study provides valuable insights into non-commuting mobility patterns using large-scale smartphone data, several limitations must be acknowledged. First, the analysis is based on aggregated origin–destination flows at the neighbourhood level, which restricts our ability to fully capture individual-level variability or motivations behind trips. Second, although we isolate non-commuting trips, the categorisation of trip purposes may still contain ambiguities, especially in overlapping activities such as shopping combined with caregiving. Third, the study is limited to Seoul, a highly transit-oriented and socioeconomically stratified city; thus, findings may not be directly generalisable to cities with different spatial forms or transit systems. Fourth, mobility patterns were examined without direct integration of spatial built environment variables, such as walkability, land use mix, or centrality, which may influence both activity space distance and diversity. Finally, while entropy and travel distance serve as useful proxies for mobility inequality, they do not capture subjective dimensions such as perceived safety, comfort, or purpose-driven constraints, factors that could enrich the interpretation of disparities across groups. These limitations underscore the need for future studies combining spatial metrics with qualitative and survey-based insights to fully understand the drivers of mobility inequality.

Additionally, while this study emphasizes income as a key factor shaping mobility, neighbourhoods with similar income levels may exhibit distinct spatial characteristics, some of which are centrally located with high accessibility. In contrast, others are more peripheral and residential. These locational differences can influence both the scale and diversity of activity spaces. Future research should therefore incorporate centrality or spatial accessibility metrics to understand better how socioeconomic and geographic factors interact to shape mobility patterns.

5.2. Conclusions

This study highlights that spatial equity in non-commuting mobility is not only a question of access, but a critical dimension of urban sustainability and social justice. By analysing activity space distance and destination diversity through entropy and Gini coefficients across different times of day, we reveal how socioeconomic factors, particularly age, gender, and income, shape both the extent and equity of mobility in Seoul. The combination of these indicators with temporal segmentation offers a novel, multidimensional perspective on urban mobility patterns, providing actionable insight into where and when mobility inequalities are most pronounced.

Looking forward, future research could build on this work by employing longitudinal data to observe how mobility patterns evolve over time in response to urban development or policy interventions. Comparative studies across cities with varying spatial forms and transport systems could also deepen understanding of contextual influences. Furthermore, integrating mobility metrics with built environment features, such as land use diversity, connectivity, or centrality, and incorporating qualitative perspectives from residents could help uncover the lived experience behind the numbers. Such approaches will be essential for designing urban environments that are not only efficient but also inclusive, responsive, and just.

Future research could also explore the underlying social, cultural, and institutional factors that shape the observed disparities in activity space distance and destination diversity, helping to unpack not just where and when disparities occur, but why they persist. For example, the widening gender gap in both mobility scale and diversity after the age of 30 warrants further examination, particularly in relation to caregiving roles, workplace expectations, or safety perceptions. Comparative studies across different cultural or urban contexts would also help to validate and expand these findings. In addition, evaluating the effectiveness of time-sensitive interventions, such as enhancing nighttime accessibility for older adults or increasing the diversity of amenities in underserved areas, could offer practical guidance for inclusive mobility planning.

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