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Unpacking urban scaling and socio-spatial inequalities in mobility: Evidence from England

Qi-Li Gao
Shenzhen University, China; University College London, UK

Chen Zhong
University College London, UK

Yikang Wang
University College London, UK

Abstract

Prior research on the scaling of city size and inequality has a primary focus on economic factors such as income. Limited research has addressed socio-spatial disparities in mobility, involving physical activities and social interactions among individuals and population groups. Utilising mobile phone app data, this study measured inequalities using multiple mobility-related indicators (i.e. the number of activity points, the radius of gyration, self-containment, and social interaction indices) and related to population size by scaling models. In England's context, these indicators unfolding mobility patterns and social issues display different scaling regimes, varying from sublinear to super-linear. It was observed that larger cities are associated with greater social interactions, particularly among socioeconomically advantaged groups; however, they also exhibit exacerbated self-segregation. Due to the radiation effect of big cities, the performances (e.g. travel radius) of small surrounding towns deviate from the predicted values of scaling models. Within cities, the evenness of indicators is independent of population size and produces distinct spatial patterns. The findings expand upon previous research and provide a more nuanced understanding of the complex relationship between city size, urban inequality, and human mobility.

Keywords

Socio-spatial inequality, human mobility, activity space, urban scaling, mobile phone app data

Corresponding author:
Chen Zhong, Centre for Advanced Spatial Analysis (CASA), University College London (UCL), London, WC1E 6BT, UK.
Email: c.zhong@ucl.ac.uk

Data Availability Statement included at the end of the article

Introduction

Comprehending how urbanisation-induced urban dynamics affect the interplay between people and society has emerged as a significant challenge. Although bigger cities generate more economic outputs, they might produce higher living costs and urban inequality, leading to the unsustainability of cities (Baum-Snow and Pavan, 2013; Sarkar, 2019). The escalation of urban inequality raises concerns about the health and livelihoods of urban residents, sparking a substantial academic debate. Previous studies focused on economic inequality, neglecting other forms of socio-spatial inequality due to limited fine-grain data. Socio-spatial inequality highlights how social and economic disparities are intertwined with spatial patterns, such as residential segregation and access to urban opportunities and services (Han, 2022; Modai-Snir and Van Ham, 2018). Human movement and daily activity spaces reveal urban resource access and segregation levels, providing a valuable opportunity for detailed empirical exploration of urban inequalities (Cagney et al., 2020; Comber et al., 2022; Gao et al., 2021).

Studying people's movement in cities of different sizes has been challenging due to lengthy data collection processes, geographic limitations, and potential sampling biases linked to traditional data collection methods. Consequently, previous studies are mainly (residential) place-centred and static, ignoring the segregation experience across various activity spaces due to the dynamism of movements (Li et al., 2022). Recently, big data capturing multiple facets of urban spaces and human behaviours provides us with better observations of daily mobility and social interactions. However, some relevant work using mobility big data is dominantly about American cities, and only a few addressed European Union cities, resulting in a big puzzle surrounding the mobility-based inequality and its potential relationship with urbanisation (Nilforoshan et al., 2023; Wang et al., 2018).

Urban scaling law has been utilised as a powerful predictive tool and quantitative theory of urban organisation, economic development, and human behaviours toward urbanisation (Bettencourt et al., 2013). Several crucial urban variables have been identified to be scale functions of city size across different countries (Li et al., 2017). The observations about scaling behaviours are particularly valuable in determining the optimal size for a city (Batty, 2008). In this sense, the existence of scaling laws of urban inequality might provide fundamental quantitative insights and predictability into underlying social processes toward urban sustainability.

This study aims to find out to what degree the growing city size could exacerbate or alleviate mobility-related inequality based on the emerging mobility phone app dataset, and whether or not follows any scaling behaviours that could be valuable in determining the optimal size for a city. Answers to this question provide substantial evidence for the development of urban inequalities in mobility and segregation in urban areas. The shifting of our attention beyond American cities not only contributes to the diversity of global urban studies but also provides a broader and more comprehensive perspective. By examining cities in England, we can compare urban development differences among various countries or regions, thereby enhancing our understanding of both common trends and unique circumstances in global urbanisation. Such an expanded view facilitates deeper academic discussions and offers insightful viewpoints and solutions for urban planning and development.

Literature review

Urban inequality

Sustainable urban development relies on diverse populations and strong social cohesion. However, cities are witnessing mounting segregation and inequality (Tammaru et al., 2020). These trends pose a threat to the economic, social and health outcomes of urban residents and the next generation

(Xu et al., 2023). Research and debate focus on the link between city size and inequality, with larger cities found to have higher levels of inequality (Florida, 2017). Although larger cities are generally more productive and prosperous, their distribution is uneven and follows a heavy-tailed pattern, particularly in comparison to smaller cities (Arvidsson et al., 2023). The highest earners saw the most substantial growth in growing cities, suggesting that urbanisation may intensify inequality (Shutters et al., 2022). According to Sarkar (2019), poverty rates among the disadvantaged population may be higher in large cities than in smaller ones. Nonetheless, a French study discovered that city size is an unreliable predictor of inequality as regression models examining the scaling law show poor statistical fitness (Cottineau et al., 2019). The conflicting findings might be attributed to the different definitions of cities and measurements of inequality.

The correlation between urban inequality and city size has been debated, but the evidence remains inconclusive. Existing studies primarily adopted economic indicators (e.g. income and wage) to measure inequality, other crucial dimensions of the phenomenon have been overlooked (Sarkar et al., 2016; Shutters et al., 2022). Equal access to urban resources is crucial in allocating resources fairly among different groups (Gao et al., 2022). Social segregation, another manifestation of urban inequality, is a threat to a city's sustainability and cannot be overlooked (Musterd et al., 2017).

Human mobility and activity space

Tracking human mobility offers a potent way to grasp urban inequality and its influence on how different socioeconomic groups interact within urban spaces (Li et al., 2022). People's movements within a space are influenced by their personal preferences, socioeconomic status (SES), demographic characteristics, safety concerns, and cultural backgrounds (Gauvin et al., 2020; Park and Kwan, 2018). Urban resources and opportunities are not equally distributed across the city or metropolitan areas. Certain neighbourhoods enjoy superior access to vital services, such as healthcare, education, and employment opportunities, while others may face a scarcity of such resources. The unequal access can significantly affect people's travel patterns, as individuals residing in areas with inadequate resources may have to travel considerable distances to access necessary services. These movements also determine one's exposure to the social environment and potential interactions with others, ultimately impacting urban inclusivity and social equality (Farber et al., 2015).

Activity space reflects the geographic areas they perform daily activities and the people they interact with in their daily lives (Zhang et al., 2019). Several studies used activity space variations to highlight how diverse socioeconomic groups are limited by their space size and the available variety of urban opportunities (Järv et al., 2015; Silm et al., 2018). The number of unique activity places is a main characteristic of the people's actual activity space. Having more activities at distinct places indicates more diverse daily life. It reflects how people take advantage of urban facilities under the complex interactions of individual preferences and spatial-temporal-social constraints. If one group travels to fewer places compared to its counterparts, it might have fewer chances to encounter others and to be more isolated as a result (Wang et al., 2018).

The radius of gyration quantifies the dispersion of one's activity space. A larger radius of gyration sometimes means a more dispersed activity space, suggesting that people have the ability (e.g. better transport accessibility, higher economic ability) to access more opportunities in a larger coverage. In this case, a large radius means an advantage. However, the trend is dependent on the context and may not have universal applicability to all urban areas (Xu et al., 2019). For example, low-income individuals may need to travel farther than their affluent counterparts (Shelton et al., 2015). Besides, compact urban structures can result in a shorter radius of gyration. When focusing on commuting activities, longer travel radii probably imply a heavy commuting burden and geographical disadvantage. Therefore, multiple indicators are combined to depict spatial inequality patterns across subpopulation groups (Gao et al., 2022). Despite the complex potential relationship with inequality, these indicators have been widely used in segregation and isolation research to enhance our understanding of whether people from varying socioeconomic backgrounds can equally benefit from the opportunities provided by cities and participate fully in society (Li et al., 2022; Müürisepp et al., 2022). With the growing usage of communication technology and location-based services over the past decade, human mobility data (e.g. Twitter and mobile positioning data) capturing real-time locations of millions of users has been an innovative data source for studying urban inequality (Gao et al., 2022; Luo et al., 2016). Despite the increasing concerns about urban inequalities in mobility, the relationship with city size remains an open question.

Urban scaling

Measuring the size of an urban system through demographic and socioeconomic processes is a fundamental theme in urban science (Sarkar, 2019). Urban scaling describes how socioeconomic and functional attributes scale with the city size, taking the power-law form of $Y = \alpha X^{\beta}$, with Y as an indicator characterising urban performance, X as the city size (e.g., total population) and β the scaling exponent. Urban scaling law has been examined from geography, urban studies, and economics domains (Dong et al., 2020). The scaling regimes can be categorised into three kinds according to their functionality and magnitude, namely, super-linear scaling (β >1), linear scaling (β ≈1) and sub-linear scaling ($\beta < 1$).

Urban scaling law holds significant implications for policymakers and urban planners as a theory explaining how urban socioeconomic activities (e.g. potent and income), urban infrastructures (e.g. road network density and building volume), and social progress (e.g. inter-city migration) related to the city size (Batty, 2013; Bettencourt et al., 2013; Prieto Curiel et al., 2018). One of the commonly acknowledged discoveries is that bigger cities are more productive and innovative than smaller ones due to the concentration of high-skilled workers (Arbesman et al., 2009; Glaeser and Resseger, 2010). Besides, contacts and communication activities grow super-linearly with the population size (Schläpfer et al., 2014). However, as the economic advantages of larger cities increase, so do other negative aspects such as travel expenses, crime rate, pollution, and inequality (Sarkar, 2019). In this sense, big cities can be either attractive or unattractive depending on the perspective. This study will explore how inequality increases with urban growth across diverse quantitative aspects. This will enhance our comprehension of the intricate links among city growth, inequality, and sustainability, facilitating appropriate interventions.

Study area and data

Study area

The study area is England, United Kingdom (UK), as shown in Figure 1(a). A total of 109 Major Towns and Cities (refer to TCITY afterward) are used as the main spatial units, whose geography is based on the built-up area dataset. TCITY focuses on the 'core' town or city rather than its surrounding area and breaks the link to administrative areas.

Extracting daily mobility from mobile phone app data

We adopted mobile phone location data gathered through in-applications and collected in March 2021. A user's location is recorded by the device's GNSS positioning or fused positioning. The data includes the unique anonymous ID of a user, timestamp, latitude, longitude, and localisation

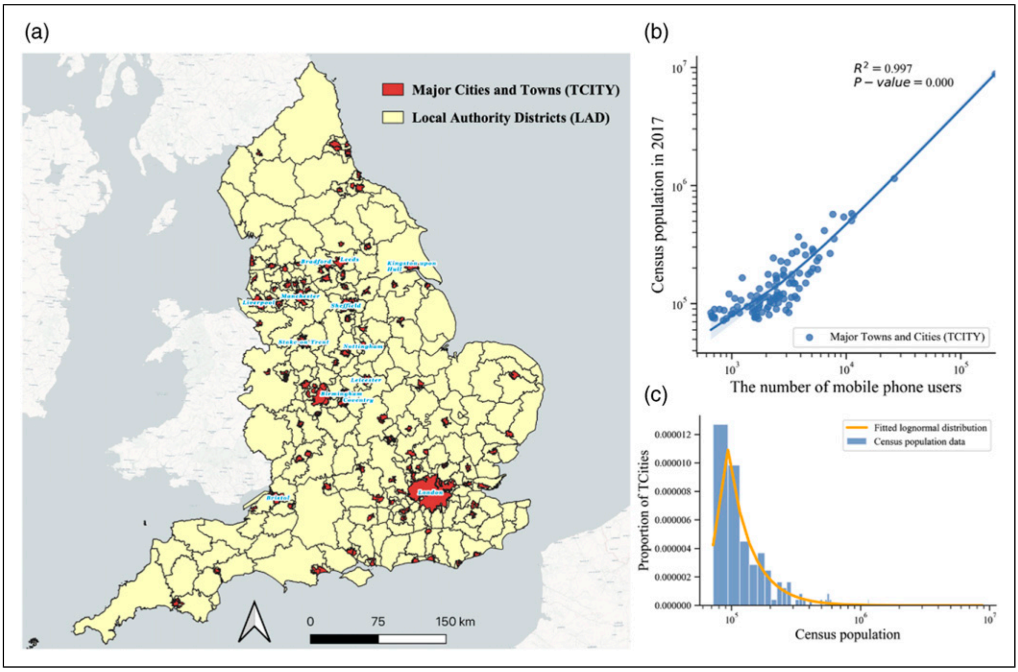

Figure 1. (a) The study area: England; (b) the correlation between the number of mobile phone users identified and census population data on a log scale; and (c) population distribution histogram.

accuracy. The raw data covers roughly 10% of the total population. We excluded users with less than 10 records in a month because their activity places could not be accurately determined. As a result, about 25% of the original users in the dataset left. Afterward, a multi-stage clustering is performed to extract the most regularly visited locations associated with daily activities (Supplemental material). The most regularly visited location is the residence, with the rest of the points treated as non-residence activity locations.

To build the relationships between population size and mobility indicators, all the mobile phone users were aggregated to the corresponding spatial units based on home locations, thus, the spatial unbiasedness serves as a prerequisite for subsequent analysis. We validated home locations by comparing them against census data. The latest TCITY-level population data was estimated in the middle of 2017. Figure 1(b) shows a very high degree of correlation with R^2 of 0.997 between the number of identified mobile phone users and the census population, demonstrating the rationality of analysing the mobility behaviours of these mobile phone users against city size in terms of representation of the whole population.

We further examined if the population size follows a power law or a log-normal distribution, as noted in previous literature (Eeckhout, 2004; Rosen and Resnick, 1980). The Maximum Likelihood Estimation (MLE) was used to fit the data more robustly, and the Kolmogorov–Smirnov test was conducted to determine which distribution of the data fits best. The results indicate that the TCITY-level population follows a log-normal distribution (Figure 1(c)).

Profiling socioeconomic status by linking Index of Multiple Deprivation data

Given that the individual SES in mobile phone data is not available to preserve individuals' privacy, research usually adopts area-based SES indicators as the approximation of individual SES, such as housing prices and median household income of their home areas (Moro et al., 2021; Xu et al., 2019). Moreover, individuals residing in the same location often share similar SES, it is feasible to infer individual SES from the information reported at the group or fine-scale aggregated level.

LSOA (Lower-layer Super Output areas)-level Index of Multiple Deprivation (IMD) decile data in 2019 is utilised to create a socioeconomic profile of mobile phone users. The IMD decile ranks LSOAs according to their level of deprivation, with 1 being the most and 10 the least deprived. We further merged 10 IMD deciles into 5 levels and labelled them to users based on home locations. We assume homogeneity among users within an LSOA unit due to its small size with an average of approximately 1,500 residents or 650 households.

The IMD data is employed in two ways. Firstly, the IMD data is utilised to compute interaction-related indices that quantify the interaction potential and segregation among different groups. Secondly, we examine how scaling effects vary from SES to gain a better understanding of the disparities that exist between different groups.

Methodology

Characterising individual-level mobility indicator

After the preliminary data process, each individual mobile user is profiled with a series of stay points and a proxied SES. Each stay point is described by $P = \{P^{t1}, P^{t2}, P^x, P^y, P^l\}$, including the starting and ending times, longitude and latitude coordinates, and the IMD level of the user. On this basis, four-dimensional mobility indicators are calculated to capture a picture of socio-spatial inequality within and across cities.

(1) The number of unique activity points (N_{stay}), describing the diversity and intensity of daily activities.
(2) Radius of gyration (R_g/km), representing the dispersion of individual activity spaces in which people travel for urban activity resources. (P_i^x, P_i^y) is the location of i^{th} activity point.

$$R_g = \sqrt{\frac{\sum_{i=1}^{N_{stay}} \left(\left(P_i^x - \overline{P^x}\right)^2 + \left(P_i^y - \overline{P^y}\right)^2 \right)}{N_{stay}}} \tag{1}$$

(3) Self-containment (S_c^{all} and $S_c^{non-home}$), revealing spatial patterns of activity locations and highlighting the extent of undertaking activities in areas adjacent to one's home. S_c^{all} and $S_c^{non-home}$ measure the proportions of all activities and non-residence activities in home-based self-contained areas, respectively. Users who have a higher self-containment tend to participate in activities in proximity to their homes.

$$S_c^{all} = \frac{\sum_{i=0}^{N_{stay}} \theta_i}{N_{stay}} \tag{2}$$

$$S_c^{non-home} = \frac{\sum_{i \in non-residence\, activities} \theta_i}{N_{stay}} \tag{3}$$

$$\theta_i = \begin{cases} 1 & if \sqrt{\left(P_i^x - P_{home}^x\right)^2 + \left(P_i^y - P_{home}^y\right)^2} \leq \text{Median}\left(R_g\right) \\ 0 & otherwise \end{cases} \tag{4}$$

(4) Social interaction potential (S_{total}/km*minutes and S_{self}), denoting the likelihood of encountering individuals from similar or different groups during daily activities. Two interaction indicators are utilised: total interaction potential (S_{total}) measures interactions among all populations; self-interaction potential (S_{self}) counts interactions within the same group. A higher self-interaction potential suggests a higher degree of isolation and lower interaction with individuals from other groups. For potential interaction to occur, two activity points must overlap in activity durations and proximity to each other (eps = 1 km). The closer the two activity points are, the greater the interaction potential. Social interaction indices are calculated below

$$S_{total} = \sum_{i=0}^{N_{stay}} \sum_{j=0}^{N} Dur^{i,j} * \left(eps - Dis^{i,j}\right) \tag{5}$$

$$S_{self} = \frac{\sum_{i=0}^{N_{stay}} \sum_{j=0}^{N} Dur^{i,j} * \left(eps - Dis^{i,j}\right) * \delta^{i,j}}{S_{total}} \tag{6}$$

$$Dur^{i,j} = \begin{cases} Max\left\{P_i^{t2}, P_j^{t2}\right\} - Min\left\{P_i^{t1}, P_j^{t1}\right\} & if\ Max\left\{P_i^{t2}, P_j^{t2}\right\} \geq Min\left\{P_i^{t1}, P_j^{t1}\right\} \\ 0 & otherwise \end{cases} \tag{7}$$

$$Dis^{i,j} = \begin{cases} \sqrt{\left(P_i^x - P_j^x\right)^2 + \left(P_i^y - P_j^y\right)^2} & if \sqrt{\left(P_i^x - P_j^x\right)^2 + \left(P_i^y - P_j^y\right)^2} \leq eps \\ 0 & otherwise \end{cases} \tag{8}$$

$$\delta^{i,j} = \begin{cases} 1 & if P_i^l = P_j^l \\ 0 & otherwise \end{cases} \tag{9}$$

where N is the total number of activity points for all users. ($\overline{P^x}$, $\overline{P^y}$) and (P_{home}^x, P_{home}^y) are, respectively, the average location and home location of a user. Median(R_g) is the median value of R_g for all the users and is set to be the radius of a self-contained area. $Dur^{i,j}$ is the overlap duration of undertaking activities i,j at a location, and $Dis^{i,j}$ is the distance between two staying points.

Aggregating at spatial units and measuring inequality

The initial investigation focuses on the total aggregation (sums) of indicators at spatial units, which measures the overall performance of cities and determines if it is the simple sum-up of individuals. The sums capture the between-city variances at the overall level when scaling to city size. However, highly skewed distributions occur within cities, thus, the sums and means are not inadequate to reveal the inequality (Arvidsson et al., 2023). Given that, we further analyse the within-city differences of the relevant indicators and their association with population size, suggesting within-city inequalities. Three inequality methods are applied to evaluate the robustness of the results. In the discrete case, if an attribute of individual i is represented as x_i, and there are N individuals, then

$$Gini = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N}\left|x_i - x_y\right|}{2N^2\overline{x}} \tag{10}$$

The Theil index is another commonly used inequality approach, which is defined as

$$Theil = \frac{1}{N}\sum_{i=1}^{N}\frac{x_i}{\overline{x}}\ln\left(\frac{x_i}{\overline{x}}\right) \tag{11}$$

The Highest-Lowest Ratio (HLR) is one of the alternative measures to examine variance, which calculates the ratio between the highest- and lowest-level groups at the mean of a certain variable

$$HLR = \frac{\overline{x_H}}{\overline{x_L}} \tag{12}$$

where $\overline{x}$ is the average of x_i. $\overline{x_H}$ and $\overline{x_L}$ are the mean values of the highest group and lowest group in attribute x.

Exploring urban scaling law

Urban scaling law entails the power-law relationship $Y = \alpha X^{\beta}$, where β is the scaling exponent, X is the population size and Y represents a mobility indicator. $\beta > 1$ is said to scale super-linearly with the population size, while $\beta \approx 1$ implies that the indicator scales proportionally linearly and $\beta < 1$ indicates a sub-linear relationship. β allows us to determine whether people in larger cities can access more activity opportunities and have higher levels of segregation than those in smaller cities.

Some studies performed log transformation on the variables and used Linear Ordinary Least-Squares regression to estimate the scaling exponent. This method has been demonstrated to suffer from some limitations (Clauset, 2009; Leitaõ, 2016). Following the study (Leitaõ, 2016), we applied MLE and bootstrap methods to generate a more robust estimation.

Results and analysis

Scaling analysis: Between-city urban inequalities

The statistics of individual mobility indicators are presented in Table A1 in the Supplemental material. The total sum of mobility indicators was first scaled against the population size. We present the estimated β along with a 95% confidence level (CI). Studies indicate that London consistently outperforms other locations across various urban indicators (Arcaute et al., 2015). As a global city situated in a relatively compact country, London's impact could extend to the entire urban system. It may be essential to assess the performance of London in comparison to other global hubs and separate it from its domestic counterparts. To validate this, we initially incorporate all major cities and towns in our models. Subsequently, we exclude London to assess the fitting of other cities.

As Figure 2 shows, N_{stay} scales sublinearly with population size when excluding London from the model, indicating that people in larger cities averagely have fewer activities compared to those residing in small towns. It could be attributed that people in large cities might spend more time working, leaving less time for extra non-mandatory activities (Sarkar, 2019). In this predicted model, London's actual value surpasses the predicted value significantly because London provides people with more diverse opportunities and amenities for daily activities. Therefore, when considering London in the model, N_{stay} presents a linear correlation with population size. An approximately sublinear relationship was observed for R_g, demonstrating that as cities expand, the

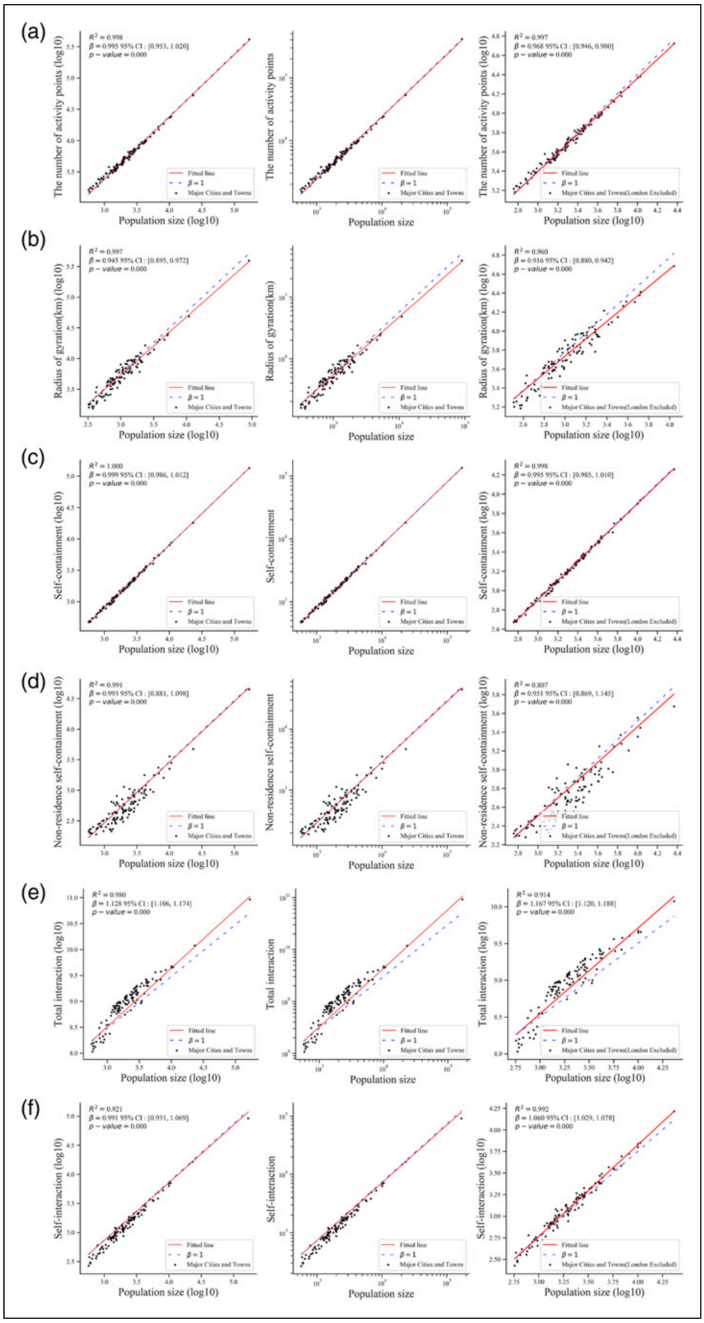

Figure 2. Urban scaling for the sum of indicators: (a) the number of activity points, (b) the radius of gyration, (c) self-containment, (d) non-residence self-containment, (e) total interaction, and (f) self-interaction. We employed MLE and bootstrap methods to estimate the scaling exponent (β) along with a 95% CI for each indicator. The R-squared values observed suggest whether population size is a good indicator for cumulative mobility indicators. Identifying a linear scaling regime is based on whether the 95% CI included 1. Our analysis involved two scenarios: initially, all major cities and towns were included in the models. The left and middle columns of the Figure depict the log-log fitting results and the fitting result on the log scale, respectively. Subsequently, we excluded London to observe the trend among other cities, as shown in the right column of the Figure. The fitted lines are illustrated in red, while the reference models, represented by β = 1, are shown as blue dashed lines.

average activity space of residents becomes more concentrated. This correlation emphasises how compact urban layouts can diminish travel requirements, enabling the fulfilment of people's activity needs within relatively confined urban environments in larger cities (Alessandretti, Aslak and Lehmann, 2020; Simini, et al., 2012).

Interestingly, people in both large and small cities had a similar tendency to spend time near home, leading to a remarkable linear relationship between S_c^{all}, $S_c^{non-home}$ and population size. A remarkable super-linear relationship was found for S_{total}, indicating that people in larger cities interact more with others. It is intuitive that higher population density in larger cities will result in high potential for social interaction during daily activities. However, S_{self} shows people in larger cities tend to interact with people from their own group, revealed by a super-linear relationship with population size when we exclude London from the model. When London is included, the parameter estimates are greatly influenced by London. To make London as close as possible to the predicted results, the values of other cities are mostly situated on one side of the predicted line (Figure 2(f): left and middle), resulting in poor fitting results, obscuring the true trend. It can be observed that the fitting results for other cities achieve a higher R-squared value, and the sample points are evenly distributed on both sides of the prediction model (Figure 2(f): right). In this predictive model, London's performance is far from the predicted values because London is one of the most diverse cities in the world, and its degree of isolation has not reached the predicted level.

A study using mobile phone mobility data shows that exposure segregation is much higher in large MSAs than in small MSAs in the US (Nilforoshan et al., 2023). Although different data sources and methods, this study discovered similar findings that big cities are characterised by high-level self-segregation. One possible explanation is that large cities offer a greater choice of differentiated spaces targeted to specific socioeconomic groups. On the contrary, different socio-economic groups in small cities tend to encounter each other more often due to limited places. The findings challenge the cosmopolitan mixing hypothesis which argues that the diverse population, constrained space and accessible public transport in large cities will increase the mixing of different socioeconomic groups, and reduce segregation.

It is also important to acknowledge that the urban scaling law is a statistical trend, and the performance of individual cities is not only determined by city size but also by other unique urban characteristics (Sarkar, 2019). As presented in Figure 2, the indicators of R_g, $S_c^{non-home}$ and S_{total} have the largest unexplained variations of observed values, thus, we depicted the distribution of residuals of the three indicators to present which cities have the greatest deviations (Figure 3) based on the calculation of $\xi_i = log \frac{y_i}{\alpha X_i^\beta}$ (Bettencourt et al., 2010). A noteworthy finding is that London

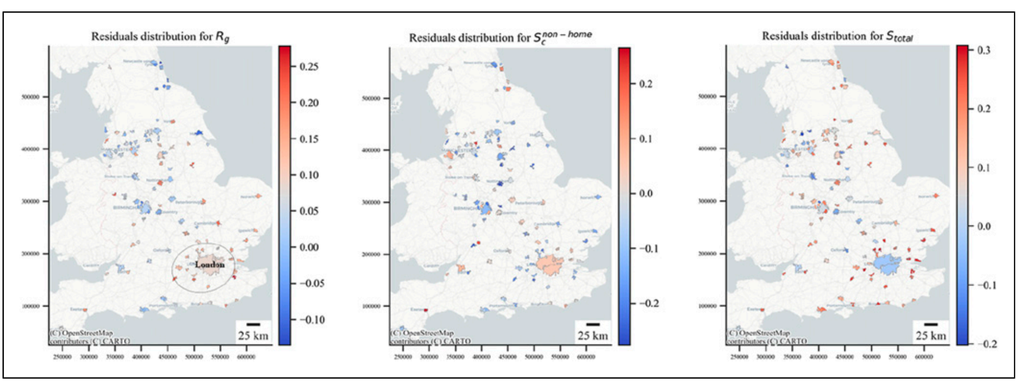

Figure 3. Residual distribution for indicators: R_g, $S_c^{non-home}$ and S_{total}.

exerts a substantial magnetic pull on the inhabitants of nearby cities and towns. This is evidenced by R_g, which is considerably larger than the predicted values using the scaling model. One possible explanation is that people living in these areas often travel to London for their daily activities. Consequently, they have a lower degree of $S_c^{non-home}$ than the average and higher S_{total} with others due to the high-density opportunities provided by London. According to new economic geography and the study (Meijers and Burgers, 2016), small cities could 'borrow size' from larger neighbours that are proximate geographically or in a network, thus presenting some characteristics of larger cities. In terms of functionalities, this study reveals some borrowed size effects. People in small cities go to nearby large cities to enjoy opportunities, and amenities and share knowledge because of good transport connectivity and geographical proximation. Other major cities may also experience these appealing and radiation effects, which could impact the overall performance of neighbouring small cities and towns. However, if there are multiple big cities nearby, the effects are likely to be more intricate.

Scaling analysis: Disparities among IMD groups

Potential variations among different socioeconomic groups are crucial because the different parts of a distribution may fall into different scaling regimes (Sarkar, 2019). The group differential is extremely important to highlight social equality. To investigate this hypothesis, we take a further step and scale the mobility indicators for each group. Because of the impacts of London identified in Figure 2, we conduct the analysis for other cities.

Figure 4 shows the scaling exponents for $S_c^{non-home}$, R_g, and S_c^{all} are not significantly associated with IMD level, while N_{stay} trend suggests that larger city size leads to a lower likelihood of conducting activities, particularly for wealthier demographics. The study observed that the less deprived groups exhibit greater super-linear scaling exponents in terms of S_{total}, indicating a greater tendency towards social interaction compared to the disadvantaged groups. Meanwhile, the scaling exponent for S_{self} has a positive relationship with the IMD level, revealing that socioeconomically

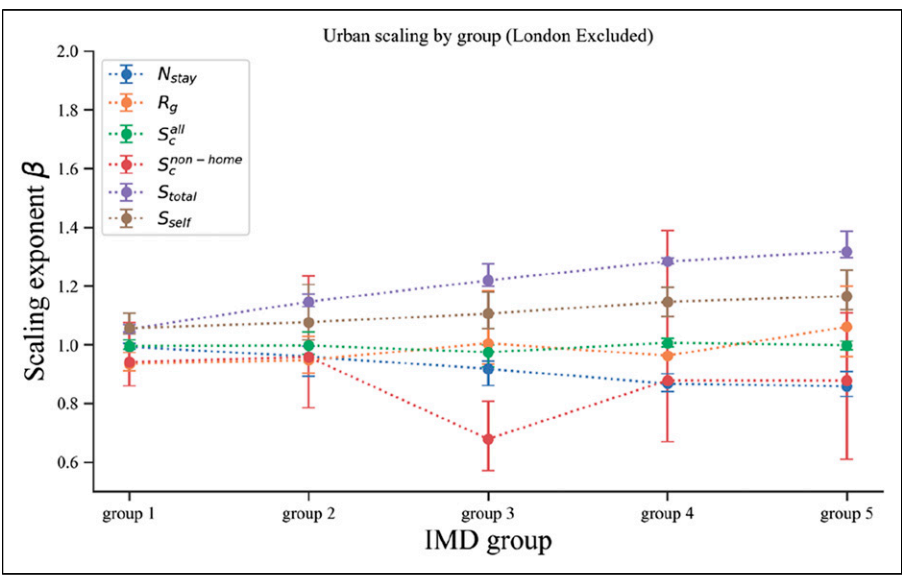

Figure 4. Urban scaling for aggregation of indicators by group.

advantaged groups are more likely to reinforce self-segregation along with urban growth. This finding explains the observed evidence that people with high socioeconomic status are the most self-segregated (Haandrikman, et al., 2023).

Scaling analysis: Within-city urban inequalities

The hypothesis assumes that larger cities display higher levels of within-city inequality, and thus, a power-law correlation between population size and the within-city difference is expected. However, the study finds that regression models yield either insignificant *p*-values and very small R^2 values across all models regarding the Gini coefficient (Figure 5). The results are consistent when using different inequality measurements (Supplemental material). That suggests that larger cities do not necessarily experience more significant within-city inequality. Another study examining the scaling law of Gini of wages and segregation index found no significant association between city size and economic inequality (Cottineau et al., 2019).

Although within-city inequalities have no significant association with population size at the England national level, there might exist some spatial clustering patterns regionally. To gain further insights into this issue, the study employed Getis and Ord's local (G*) statistic method on the Gini coefficients (Supplemental material). Figure 6 reveals varying spatial clustering patterns for different indicators across England. Overall north-south divisions were revealed for indicators, N_{stay}, S_{total}, and S_{self}. To be specific, core urban areas in northern England present high levels of within-city inequality in S_{total}, but low levels in N_{stay} and S_{self}, while southern urban areas exhibit the opposite pattern. In particular, S_c^{all} displayed high-value clusters in the areas surrounding Birmingham, the second largest metropolitan city of England, while R_g showed low-value clusters in

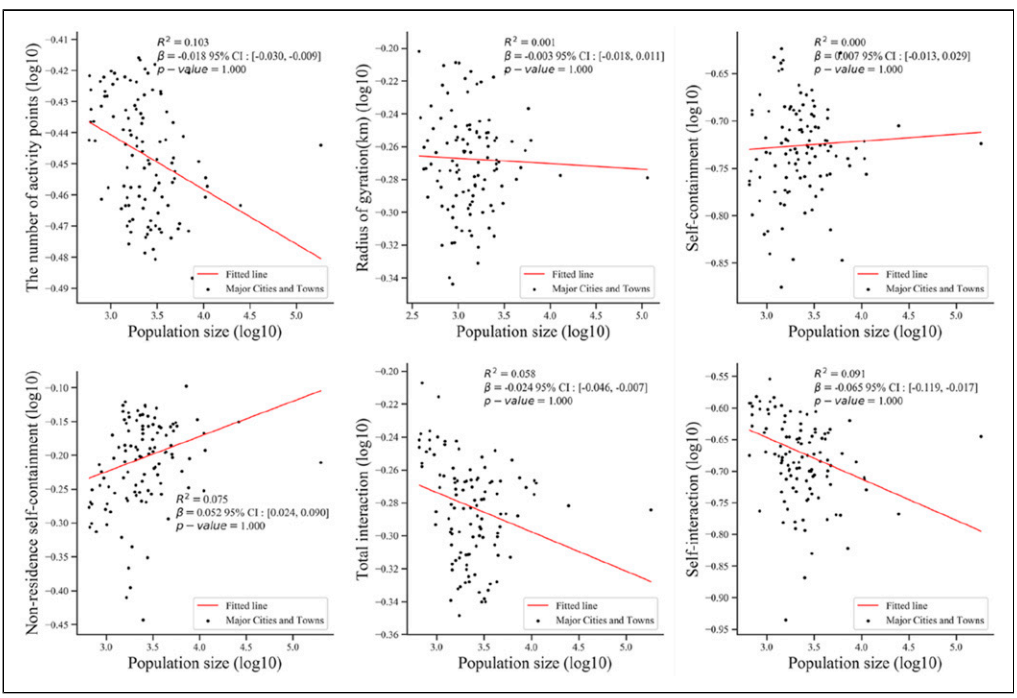

Figure 5. Urban scaling for Gini coefficient of indicators.

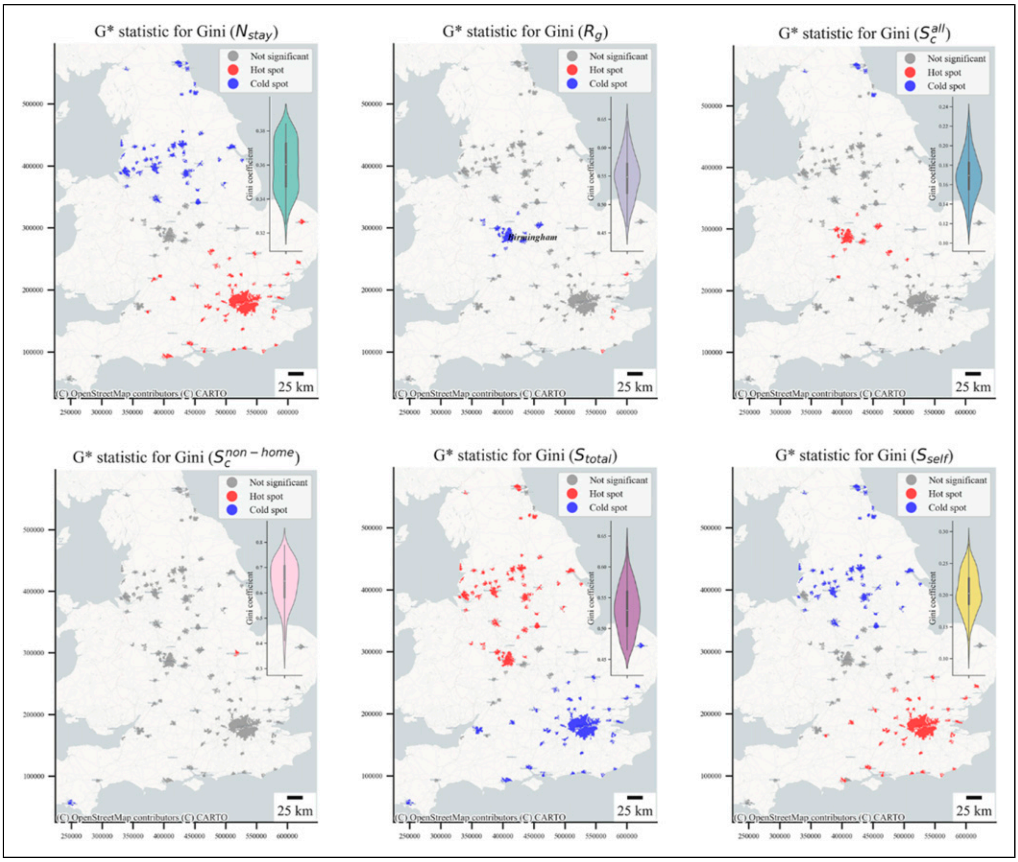

Figure 6. Spatial clusters of the Gini coefficient for indicators.

partial areas of the same region. No significant spatial clustering pattern was identified for the indicator with high Gini values, $S_c^{non-home}$. The observed variations suggest that there may be different factors (e.g. spatial structure and topology) contributing to spatial inequalities in urban areas. These findings underscore the complex nature of within-city inequalities and regional unbalanced developments driving mobility characteristics, informing more targeted policy interventions.

Discussion and conclusion

As cities grow bigger, striking a balance between higher productivity and greater inequality becomes a challenge. While larger cities can provide more avenues for wealth and prosperity, they can also worsen current social inequalities and create new ones (Rybski et al., 2019). Though there have been many observations indicating that larger cities are more economically unequal than their regional or national averages, the evidence is inadequate in terms of the multifaceted nature of inequality (Sarkar et al., 2016). Extensive analysis is necessary to expand our understanding of urban systems and the social process, which can help advance the understanding of urban growth and the quantitative theory of the average city. By studying the relationship between urban size and inequality, researchers can identify strategies for promoting more equitable access to urban opportunities and resources.

The study explored urban scaling laws of urban inequality from a human mobility perspective beyond conventional economic characteristics. The indicators, especially social interaction, are innovative as they are applied to dynamic activity space rather than static residential space. Our findings indicated that different measures of mobility behaviour produced diverse scaling patterns. On the one hand, the concentration of individuals in large urban areas typically increases social interaction among the residents. On the other hand, the level of self-segregation also increases with population size. In addition, our in-depth analysis of the disparity among different groups found that certain groups may be subject to advantages or disadvantages within urban environments, which can ultimately contribute to patterns of urban inequality in the long run. Urban planning has the potential to alleviate segregation. The locating of commonly used urban amenities like transportation hubs, plazas, shopping centres, and parks near diverse neighbourhoods would create opportunities for residents of various socioeconomic backgrounds to interact as they frequently share these spaces. Meanwhile, evidence shows that segregation in residential places is more significant than in other activity places, thus some particular intervention strategies like mixing housing policies could be considered to increase the chances of interactions and building social networks with one another (Gao et al., 2024; Nilforoshan et al., 2023). This study also serves as a reminder to urban planners that amidst urbanisation, special attention must be paid to preventing major cities from further evolving into machines that breed segregation.

The relationship between within-city inequalities and city size is not significant, suggesting that urban growth is more likely to increase between-city inequalities other than within-city inequalities, emphasising the significance of measuring and comprehending the multiple facets and underlying nature of social progress. By investigating the spatial distribution of the within-city inequalities, this study also found distinct spatial clustering patterns across different mobility characteristics. Particularly, a clear north-south regional variance has been observed. The identified spatial clustering patterns suggest that specific urban areas may require tailored solutions to address the underlying causes of inequality. For instance, while promoting activity opportunities and affordable housing may be effective in reducing inequalities related to activity intensity and self-interaction in some southern urban areas, it may not be sufficient to address the underlying factors driving inequality in northern urban areas characterised by high levels of total interaction. Thus, a more nuanced understanding of spatial clustering and the mobility indicators driving them is critical for designing more effective policies aimed at promoting inclusive urban development.

Research on urban scaling relations can offer valuable insights into the complex social organisation and dynamics that underlie the urban growth and development (Bettencourt et al., 2013). In addition to measuring population size, future studies may use alternative metrics to capture the complexity of urban environments and social dynamics. For example, researchers may consider using the number of jobs, housing units, or urban amenities as proxies for urban size. By developing more nuanced and accurate measures of urban growth and development, researchers can better understand the challenges and opportunities associated with urbanisation and work towards creating more sustainable and equitable cities.

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ORCID iDs

Qi-Li Gao https://orcid.org/0000-0003-0179-3500
Yikang Wang https://orcid.org/0000-0001-6467-5953

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Supplemental Material

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References

Alessandretti L, Aslak U and Lehmann S (2020) The scales of human mobility. *Nature* 587(7834): 402–407.

Arbesman S, Kleinberg JM and Strogatz SH (2009) Superlinear scaling for innovation in cities. *Physical Review E: Statistical, Nonlinear, and Soft Matter Physics* 79: 016115.

Arcaute E, Hatna E, Ferguson P, et al. (2015) Constructing cities, deconstructing scaling laws. *Journal of the royal society interface* 12(102): 20140745.

Arvidsson M, Lovsjö N and Keuschnigg M (2023) Urban scaling laws arise from within-city inequalities. *Nature Human Behaviour* 7: 365–374.

Batty M (2008) The size, scale, and shape of cities. *Science* 319: 769–771.

Batty M (2013) Sociology. A theory of city size. *Science* 340: 1418–1419.

Baum-Snow N and Pavan R (2013) Inequality and city size. *The Review of Economics and Statistics* 95: 1535–1548.

Bettencourt LMA (2013) The origins of scaling in cities. *Science* 340: 1438–1441.

Bettencourt LMA, Lobo J, Strumsky D, et al. (2010) Urban scaling and its deviations: revealing the structure of wealth, innovation and crime across cities. *PLoS One* 5: e13541.

Cagney KA, York Cornwell E, Goldman AW, et al. (2020) Urban mobility and activity space. *Annual Review of Sociology* 46: 623–648.

Clauset A, Shalizi CR and Newman MEJ (2009) Power-law distributions in empirical data. *SIAM Review* 51(4): 661–703.

Comber S, Park S and Arribas-Bel D (2022) Dynamic-IMD (D-IMD): introducing activity spaces to deprivation measurement in London, Birmingham and Liverpool. *Cities* 127: 103733

Cottineau C, Finance O, Hatna E, et al. (2019) Defining urban clusters to detect agglomeration economies. *Environment and Planning B: Urban Analytics and City Science* 46: 1611–1626.

Dong L, Huang Z, Zhang J, et al. (2020) Understanding the mesoscopic scaling patterns within cities. *Scientific Reports* 10: 21201.

Eeckhout J (2004) Gibrat's law for (all) cities. *The American Economic Review* 94: 1429–1451.

Farber S, O'Kelly M, Miller HJ, et al. (2015) Measuring segregation using patterns of daily travel behavior: a social interaction based model of exposure. *Journal of Transport Geography* 49: 26–38.

Florida R (2017) *The New Urban Crisis: How Our Cities Are Increasing Inequality, Deepening Segregation, and Failing the Middle Class-And what We Can Do about it*. Hachette UK: Basic Books.

Gao Q-L, Yue Y, Tu W, et al. (2021) Segregation or integration? Exploring activity disparities between migrants and settled urban residents using human mobility data. *Transactions in GIS* 25: 2791–2820.

Gao Q-L, Yue Y, Zhong C, et al. (2022) Revealing transport inequality from an activity space perspective: a study based on human mobility data. *Cities* 131: 104036.

Gao Q-L, Zhong C, Yue Y, et al. (2024) Income estimation based on human mobility patterns and machine learning models. *Applied Geography* 163: 103179.

Gauvin L, Tizzoni M, Piaggesi S, et al. (2020) Gender gaps in urban mobility. *Humanities and Social Sciences Communications* 7: 11.

Glaeser EL and Resseger MG (2010) The complementarity between cities and skills. *Journal of Regional Science* 50: 221–244.

Haandrikman K, Costa R, Malmberg B, et al. (2023) Socio-economic segregation in European cities. A comparative study of Brussels, Copenhagen, Amsterdam, Oslo and Stockholm. *Urban Geography* 44(1): 1–36.

Han S (2022) Spatial stratification and socio-spatial inequalities: the case of Seoul and Busan in South Korea. *Humanities and Social Sciences Communications* 9: 23.

Järv O, Müürisepp K, Ahas R, et al. (2015) Ethnic differences in activity spaces as a characteristic of segregation: a study based on mobile phone usage in Tallinn, Estonia. *Urban Studies* 52: 2680–2698.

Leitaõ JC, Miotto JM, Gerlach M, et al. (2016) Is this scaling nonlinear? *Royal Society Open Science* 3: 150649.

Li R, Dong L, Zhang J, et al. (2017) Simple spatial scaling rules behind complex cities. *Nature Communications* 8: 1841.

Li Q-Q, Yue Y, Gao Q-L, et al. (2022) Towards a new paradigm for segregation measurement in an age of big data. *Urban Informatics* 1: 5.

Luo F, Cao G, Mulligan K, et al. (2016) Explore spatiotemporal and demographic characteristics of human mobility via Twitter: a case study of Chicago. *Applied Geography* 70: 11–25.

Meijers EJ, Burger MJ and Hoogerbrugge MM (2016) Borrowing size in networks of cities: city size, network connectivity and metropolitan functions in Europe. *Papers in Regional Science* 95(1): 181–198.

Modai-Snir T and van Ham M (2018) Neighbourhood change and spatial polarization: the roles of increasing inequality and divergent urban development. *Cities* 82: 108–118.

Moro E, Calacci D, Dong X, et al. (2021) Mobility patterns are associated with experienced income segregation in large US cities. *Nature Communications* 12(1): 4633.

Musterd S, Marcińczak S, van Ham M, et al. (2017) Socioeconomic segregation in European capital cities. Increasing separation between poor and rich. *Urban Geography* 38: 1062–1083.

Müürisepp K, Järv O, Tammaru T, et al. (2022) Activity spaces and big data sources in segregation research: a methodological review. *Frontiers in Sustainable Cities* 4: 861640.

Nilforoshan H, Looi W, Pierson E, et al. (2023) Human mobility networks reveal increased segregation in large cities. *Nature* 624: 586–592.

Park YM and Kwan M-P (2018) Beyond residential segregation: a spatiotemporal approach to examining multi-contextual segregation. *Computers, Environment and Urban Systems* 71: 98–108.

Prieto Curiel R, Pappalardo L, Gabrielli L, et al. (2018) Gravity and scaling laws of city to city migration. *PLoS One* 13: e0199892.

Rosen KT and Resnick M (1980) The size distribution of cities: an examination of the Pareto law and primacy. *Journal of Urban Economics* 8: 165–186.

Rybski D, Arcaute E and Batty M (2019) Urban scaling laws. *Environment and Planning B: Urban Analytics and City Science* 46: 1605–1610.

Sarkar S (2019) Urban scaling and the geographic concentration of inequalities by city size. *Environment and Planning B: Urban Analytics and City Science* 46: 1627–1644.

Sarkar S, Phibbs P, Simpson R, et al. (2016) The scaling of income distribution in Australia: possible relationships between urban allometry, city size, and economic inequality. *Environment and Planning B: Urban Analytics and City Science* 45: 603–622.

Schläpfer M, Bettencourt LM, Grauwin S, et al. (2014) The scaling of human interactions with city size. *Journal of the Royal Society Interface* 11: 20130789.

Shelton T, Poorthuis A and Zook M (2015) Social media and the city: rethinking urban socio-spatial inequality using user-generated geographic information. *Landscape and Urban Planning* 142: 198–211.

Shutters ST, Applegate JM, Wentz E, et al. (2022) Urbanization favors high wage earners. *Npj Urban Sustainability* 2: 6.

Silm S, Ahas R and Mooses V (2018) Are younger age groups less segregated? Measuring ethnic segregation in activity spaces using mobile phone data. *Journal of Ethnic and Migration Studies* 44: 1797–1817.

Simini F, González MC, Maritan A, et al. (2012) A universal model for mobility and migration patterns. *Nature* 484(7392): 96–100.

Tammaru T, Marcin´Czak S, Aunap R, et al. (2020) Relationship between income inequality and residential segregation of socioeconomic groups. *Regional Studies* 54: 450–461.

Wang Q, Phillips NE, Small ML, et al. (2018) Urban mobility and neighborhood isolation in America's 50 largest cities. *Proceedings of the National Academy of Sciences of the United States of America* 115(30): 7735–7740.

Xu Y, Belyi A, Santi P, et al. (2019) Quantifying segregation in an integrated urban physical-social space. *Journal of the Royal Society Interface* 16(160): 20190536.

Xu Y, Olmos LE, Mateo D, et al. (2023) Urban dynamics through the lens of human mobility. *Nature Computational Science* 3: 611–620.

Zhang X, Wang J, Kwan MP, et al. (2019) Reside nearby, behave apart? Activity-space-based segregation among residents of various types of housing in Beijing, China. *Cities* 88: 166–180.

Qi-Li Gao is an Assistant Professor of Shenzhen Audencia Financial Technology Institute (SAFTI), Shenzhen University (SZU). She received her PhD in GIS from Wuhan University, China. Her research interests include spatial-temporal data mining, urban inequality, and human mobility analytics toward urban sustainability and human-centred urban planning.

Chen Zhong is an Associate Professor in Urban Analytics at CASA, UCL. Her research interests lie in spatial data analysis, machine learning, urban modeling, and data-driven methods for urban and transport planning.

Yikang Wang is a PhD at CASA, UCL, supervised by Dr Chen Zhong and Prof Michael Batty. He obtained a BEng in GIS from Wuhan University with honour, followed by an MSc in Computational Science at Imperial College London. He is working on the analysis of human mobility in the UK.