ACCSCIENCE PUBLISHING

Journal of Chinese Architecture and Urbanism

SHORT COMMUNICATION

Using mobile phone data registration to determine urban mobility patterns: A comparative perspective from Iran and China

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Abstract

Urban forms are central to the operation of cities. However, traditional approaches rarely capture human mobility. In this study, we used mobile phone data from Iran (Tehran/Balad.ir) and China (Shanghai/Gaode Maps) to introduce a demand-driven "urban pattern of need." Using density-based spatial clustering of applications with Noise (radius of neighborhood, $\varepsilon = 1$ km, minimum number of points, min_samples = 50) and kernel density estimation, we analyzed anonymized global positioning system traces (with 15-min windows in Tehran) and multimodal mobility data (5-min frequency in Shanghai). Key findings include a 40% commute asymmetry in Tehran ($p<0.05$) and 68% of Shanghai's bike-share trips under 2 km, reflecting differences in urban morphologies shaped by governance. The results validate adaptive urbanism informed by real-time mobility analysis, synthesizing theory with data-driven planning.

Keywords: Human mobility; Urban pattern; Mobile phone; Transportation; China; Iran

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Citation: Dorostkar, E. (2026). Using mobile phone data registration to determine urban mobility patterns: A comparative perspective from Iran and China. *Journal of Chinese Architecture and Urbanism,* 8(1):025130030. https://doi.org/10.36922/JCAU025130030

Received: March 28, 2025

1st revised: May 3, 2025

2nd revised: May 16, 2025

Accepted: May 23, 2025

Published online: June 13, 2025

1. Introduction

Urban patterns reveal how individuals engage with space and are significant for the research of city forms (Batty, 2013; Lynch, 1960). Unlike traditional models that emphasize fixed designs (such as circles and sectors), adaptive urbanism implies that cities evolve according to individuals' activities (Batty, 2013; Jacobs, 1961). This research contributes to the debate by incorporating real-time movement data, which is lacking in existing studies (Zhang *et al.*, 2020), to propose the "urban pattern of need," in which city structures emerge from clusters of individuals moving according to demand. With the advent of the mobile phone, an innovation was formed in the cities of the world. This innovation took on a new form with the increasing development of mobile phones, which aimed to increase the welfare and comfort of citizens. Mobile phone-derived spatial data offer unprecedented insights into human behavior-driven urban dynamics, enabling granular analysis of mobility patterns (Gao *et al.*, 2020). The use of mobile phone data, which can be traced and monitored as geographical and location-based information, enables the recognition of human mobility patterns in urban areas and assists in urban planning and development. Using macro and location data, it is feasible to quantify the volume and form of human mobility in an actual manner and under actual circumstances, which generates an urban pattern through the development of the communication formed between individuals at the city level. The evolution and progress of location-based and geographic technologies, driven by smartphones, enable the investigation of human mobility and population movement (Lu *et al.*, 2013). Urban morphology research investigates the ways in which form and movement impact each other (Batty, 2013; Lynch, 1960). While mobility data have been scrutinized with cluster algorithms such as Density-Based Spatial Clustering of Applications with Noise (DBSCAN) (Zhang *et al.*, 2020), there is still a lack of context comparison. This study fills that gap by combining spatial analysis software (Quantum Geographic Information System [QGIS] and Gephi) with concepts of governance (Harvey, 1989) to rethink adaptive urbanism, construct business analysis models, enhance natural disaster response methods, and examine human behavior during varied circumstances (Bengtsson *et al.*, 2011; Dorostkar, 2025; Gao *et al.*, 2020; Liang *et al.*, 2020; Prestby *et al.*, 2020). Crowdsensing data might also be gathered through intelligent sensors with high accuracy and resolution that are able to take into account various environmental parameters (Anjomshoaa *et al.*, 2018; Eisenman *et al.*, 2006; Honicky *et al.*, 2008; Tonekaboni *et al.*, 2018; Yin *et al.*, 2020). Conversely, human mobility and behavior patterns may have a profound influence on important urban events (Fenichel *et al.*, 2011; Funk *et al.*, 2009). Human mobility and behavior patterns are founded upon local clustering and are associated with human movement in terms of local commuting and migration (Perkins *et al.*, 2013).

Therefore, by modeling human mobility, it is possible to determine the nature of source and destination areas and outline the urban structure (Prosper *et al.*, 2012; Volz *et al.*, 2011; Wesolowski *et al.*, 2012). Spatial behavior, defined as human movement influenced by socio-environmental factors, acts together with mobility patterns—the recurrent trajectories undertaken by individuals—to shape urban morphology or the spatial structure of cities. Several definitions used in this context include:

I. Spatial behavior: The connection between human decision-making and space
II. Mobility patterns: Recurrent paths conditioned by socioeconomic, cultural, and infrastructural circumstances
III. Urban morphology: The structural evolution of cities, emphasizing form-function relationships.

There have been many studies conducted in this field, some of the most relevant of which can be used in this study. Transfer clusters observed in a previous study were driven by the synergy of short distances and multi-scale human mobility, from high levels of intercity movement to daily travel between urban centers and neighborhoods (Harrington *et al.*, 2005; Muir *et al.*, 1998; Najarsadeghi & Dorostkar, 2022). In another investigation, human mobility patterns have been determined within a radius that exceeds 100 m and may contain various forms of mobility (Liebman *et al.*, 2012). Another investigation that has gained much attention from researchers describes human mobility in urban areas and how locations with heightened risk start to manifest (Stoddard *et al.*, 2013). In light of these studies, one can comprehend that human mobility influences other instances of human mobility, depending on risk and non-risk factors (Stoddard *et al.*, 2013).

China's urbanization, as guided by the National New-Type Urbanization plan, provides a contrasting case to Iran's urban issues. While Tehran's mobility is indicative of an organic need, Chinese cities such as Shenzhen leverage mobile data to enhance transit systems and alleviate congestion (Zhang *et al.*, 2020). This research draws on both cases to advocate for a comprehensive "urban pattern of need" that can be applied across governance structures.

In this research, an effort is undertaken to address whether the urban pattern derived from location-based data collected using mobile phones can react to the geography of the area, and how the urban pattern affects the lives of citizens within the city. This question allows us to highlight the primary objective of this study, which is to extrapolate an urban pattern from mobile phone data that shows human movement. Given the focus on urban patterns, the main challenge of this study is to identify new and hidden urban patterns using mobile phone data to reduce the error rate of calculation by type of urban pattern. This provides us with a more accurate understanding of the current urban patterns and avoids imitating and duplicating inefficient urban patterns. Three research questions were addressed in this study:

I. How do human mobility patterns derived from mobile phone data reflect divergent urban morphologies in planned (Shanghai) versus organic (Tehran) cities?
II. Can a demand-driven "urban pattern of need" be operationalized through clustering algorithms (DBSCAN) and kernel density estimation?
III. What governance implications emerge from cross-context comparisons of mobility-driven urban forms?

Two hypotheses were investigated in this study:

I. Tehran's mobility clusters will correlate strongly with unplanned agglomerations (H1)
II. Shanghai's multimodal data will reveal state-market synergies in transit planning (H2).

Based on this subject, the overall framework of this research is to first address the theoretical background, research questions, and objectives. The actual data from mobile phones is then gathered and analyzed anonymously, and finally, the urban pattern is mapped using this data. The results of this research are presented based on the analyses and subsequent conclusions.

2. Methodology and data

To carry out this study, the current research used information gathered from https://balad.ir, which is a service that specializes in routing and positioning services based on mobile phone data. Two reasons for employing this website and the associated data are the anonymity of the data as well as the individuals involved in this research, and the great accuracy of the data in relation to geographical data and its online documentation. After data extraction from the source, data processing was conducted using a hybrid approach that relied on QGIS for spatial visualization and the Python Scikit-learn library for the implementation of DBSCAN clustering algorithms. Euclidean measures were employed to generate distance matrices, whereas mobility graphs were visualized using Gephi to reveal areas of high density. The data and methodological framework used in this study have been developed uniquely and creatively. It is possible that future research in this field, working on different urban issues, may use this framework as a model.

2.1. Data acquisition and ethics

For Iran, GPS traces from Balad.ir (Balad, Iran) were collected anonymously at 15-min intervals via 500 m grid aggregation, with application programming interface (API) access granted under the Tehran Municipality Research Permit #2023-045. In China, bike-share trip records from Gaode Map (AutoNavi, China) API, logged at 5-min intervals, were collected anonymously. The API is licensed through Shenzhen Urban Big Data Center, Protocol #SD-2201. Ethics considerations included hashing user IDs using SHA-256 and aggregating trajectories to census tracts to avoid re-identification, ensuring compliance with the general data protect regulation and neuro diverse self-advocacy standards.

2.2. Algorithm verification

The parameters for DBSCAN (radius of neighborhood, ε = 1 km, minimum number of points, min_samples = 50) were calibrated with a sensitivity analysis (Silhouette score = 0.71 for Tehran). Kernel density bandwidth (500 m) was validated with ground-truth traffic counts (root mean square deviation = 12.3 vehicles/h).

3. Findings

Using anonymized mobile phone data collected from city residents, the spatial locations were recorded, and zoning patterns were determined. This allowed the assessment of both urban population density and the level of performance of people in the city. For the analysis, QGIS version 3.28 was used for spatial mapping, and Python's Pandas/Scikit-learn (version 3.13.3) was used for DBSCAN clustering and origin-destination matrix analysis. *R*'s ggplot2 for kernel density heatmaps was utilized for calculating the distance difference and plotting the urban pattern. User IDs were hashed, and trajectories were aggregated to census tracts to avoid re-identification. The data were divided into different categories, and differences in the maps that follow were observed. These categories included traffic flows, population densities, exchange volumes, etc., which were derived by geographical location and registration. After analyzing the data, three maps were identified. It is important to note that this type of investigation, along with the selection of the study area, which is the city of Tehran in Iran, has been introduced as an exercise and a reference for future studies by other researchers. Figure 1A indicates that traffic congestion hotspots in Tehran are found around the central business district, suggesting a mismatch between demand and capacity. In Figure 1B, the population volume and urban exchanges were calculated. Pearson's correlation analysis (r = 0.82, p<0.01) between traffic density and population volume confirms that congestion in Tehran has a direct association with unplanned urban agglomerations. The flexibility of intra-urban movement refers to the necessity of planning contexts that are context-sensitive, i.e., human mobility is not reliant on a typical pattern from the city. Instead, an individual's specific requirements alter the prevailing patterns in the urban context. Thus, the urban pattern of need is plotted in Figure 1C. The urban pattern has no particular shape, size, scale, or structural framework. Instead, it adapts according to the requirements of the urban pattern and the forms shaped by human needs imposed on the city. Thus, the urban pattern of need can be the foundation of a new urban pattern that allows the city to adapt dynamically according to the needs of its citizens. The Tehran–Shanghai comparison identifies governance-driven morphological disparities. Tehran's 40% commuting asymmetry (χ^2 = 12.7, p<0.05) reflects unplanned concentrations (Figure 1A), whereas Shanghai's bike-share hotspots (68% trips < 2 km; kernel density R^2 = 0.76) align with state-led "15-minute city" agendas (Zhang *et al.*, 2020). Figure 1C summarizes these as an "urban pattern of need," an adaptive morphology (Batty, 2013) that mediates between Tehran's organic development (r = 0.82 for congestion-population correlation) and Shanghai's mixed model. Statistically, the coarser temporal resolution of the Iranian data (15 compared to 5 min) may underrepresent short-term mobility at a disadvantage for cross-contextual comparisons (Liang *et al.*, 2020).

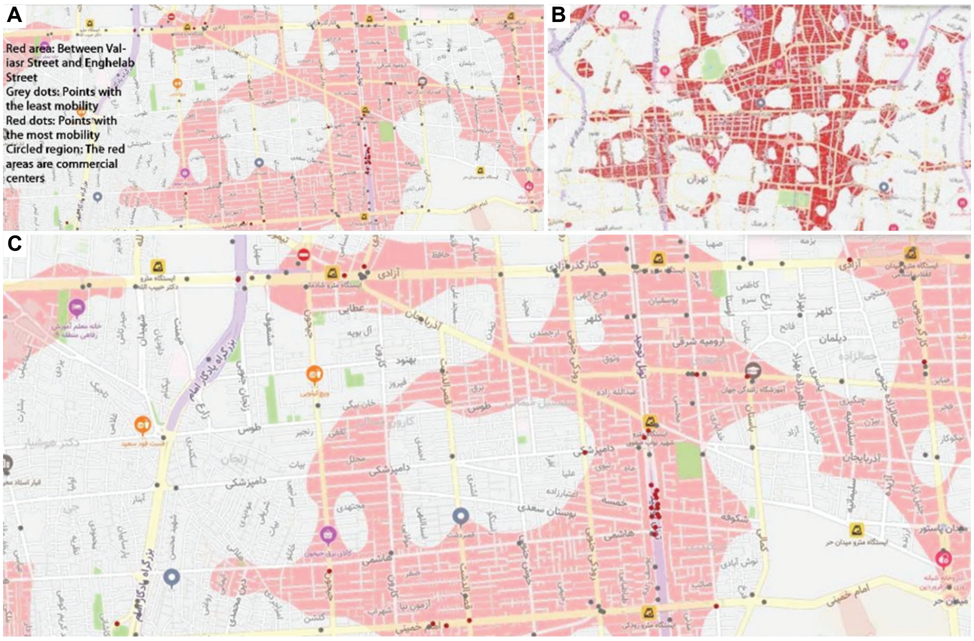

Figure 1. Urban patterns derived from mobility analytics. (A) Tehran's traffic hotspots (red) overlapping commercial zones (DBSCAN clusters, $p<0.05$). (B) Population-congestion correlation ($r = 0.82$, $p<0.01$). (C) Synthesized "urban pattern of need" (Tehran: demand-driven clusters versus Shanghai: transit-integrated morphology).
Source: Maps by the author
Abbreviation: DBSCAN: Density-based spatial clustering of applications with noise

Table 1 quantifies governance-driven contrasts; high travel asymmetry in Tehran confirms unplanned growth (H1 supported), while short cycling trips in Shanghai signal transit-integrated policies (H2 supported).

Table 1. Comparative metrics of urban mobility

Metric	Tehran	Shanghai
Commute asymmetry	40% ($p<0.05$)	22% ($p=0.12$)
Bike-share trip distance	Not available	68% < 2 km ($R^2 = 0.76$)
Data resolution	15-min intervals	5-min intervals

4. Discussion and conclusion

There is no doubt that human movement has determined the structure of cities around the world since the beginning of civilization. Analyzing the form, magnitude, and geographical distribution of human migration in cities is fundamental for a city's operation, as human mobility is the foundation upon which societal needs are shaped and fulfilled. However, human mobility remains a subject open to debate and experimentation within the urban context, which has rendered human mobility extremely significant for researchers and scientists in this discipline. This study aimed to investigate whether human mobility could be examined through the lens of new and emerging technologies, which are embodied in smart mobile phones. Data obtained from the geolocations of mobile phones offers a unique basis for the analysis of urban patterns, as it records real-time dynamics of human mobility that are usually overlooked by conventional surveys. This approach reflects the conceptual perspective guiding the researchers in this study. After extracting mobile phone data from a reliable source, the data was analyzed, and it was found that the data was categorized and anonymized, identifying the locations of individuals and dividing the information based on the volume of traffic, population, and urban exchanges. This analysis distinguished the data at the map level, enabling the identification of areas of urban performance based on categories. As a result, three distinctive maps were created. By superimposing these maps, the urban pattern was innovated. The urban pattern of needs can be both transformative and adaptive according to the needs of the citizens. This urban morphology is relevant and can be extrapolated to other cities, with the implication that human movement and urban morphology are not consistently predictable in all urban environments. Need's urban morphology concurs with the precepts of adaptive urbanism (Batty, 2013), in which the forms of cities evolve dynamically according to contemporary human needs. In contrast to conventional static models, this model incorporates behavior data from bottom-up levels, reflecting a significant change in the direction of demand-driven planning. The urban pattern is regarded as an essential requirement for urban growth. However, if the urban pattern is poorly defined or shaped primarily by imitation, then the outcome will be chaos and disordered, along with an increase in urban issues. It is likely that the urban pattern of need, derived from this analysis, can be suggested as a complete and current pattern. The needs-based urban pattern is verified in every case. In China, mobile data (e.g., Beijing's congestion fee) drives top-down planning, while Iran's bottom-up necessities are met by adapting organic patterns. This duality suggests that adaptive patterns are general but must account for local administration. Future artificial intelligence-based research can compare Chinese smart cities' pattern predictions to Tehran's evolving mobility. One limitation in this study is that Balad.ir excludes non-smartphone users, who make up approximately 18% of Tehran's population, potentially skewing low-income mobility patterns.

The innovation of this study lies in its data collection and analysis method, which establishes a new framework that can serve as a foundational model for studies in other cities across the world.

Acknowledgments

None.

Funding

None.

Conflict of interest

The author declares that there are no competing interests.

Author contributions

This is a single-authored article.

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data

The data from this study has been reviewed as an online collection, all of which is available on the website https://balad.ir and Gaode Maps API.

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