Mapping Behavioral Spatial Interactions from Individual Human Mobility Data

Meicheng Xiong [1], Sheng Wang [1], Zhongfu Ma [1], Jacob Harris [1] and Di Zhu [1]*

[1] Department of Geography, Environment and Society, University of Minnesota, Twin Cities, Minneapolis, USA
* dizhu@umn.edu

Keywords: behavioral spatial interactions, human mobility, activity type, network analysis, distance decay

Introduction

People move through cities for a variety of daily activities that meet their diverse life demands (Wheeler 1972; Mokhtarian and Salomon 2001). Such movements form intra-city flows between locations, reflecting collective patterns of spatial interactions across multiple scales. Investigating the characteristics (Yang et al. 2019), structures (Guo 2009), and laws of spatial interactions (Wilson 1971; Schläpfer et al. 2021) has attracted significant attention, as it is fundamental to understanding human mobility shaped by urban spatial elements (Pappalardo et al. 2023). This knowledge supports human-centered transportation and urban planning while promoting mobility and accessibility equity (Nilforoshan et al. 2023; Xu et al. 2025).

The increasing accessibility of large-scale human tracing data (Liu et al. 2015; Welch and Widita 2019) has enabled flexible inference of individual movements across both space and time. A plethora of studies have examined spatial interactions reflected in such inferred human mobility data by analyzing and modeling their overall patterns (Tang et al. 2015; Koylu and Guo 2017), revealing their network structures (Belyi et al. 2017; Im and Ko 2026), and investigating multiple driving factors (Ioannou et al. 2025). These efforts span across various topics, such as social networks (Koylu et al. 2021) and disease migration (Zhu et al. 2021; Andris et al. 2023), across global, regional, and local scales, grounded in spatial heterogeneity and distance decay forms (Šveda and Madajová 2023; Verma and Ukkusuri 2025). Despite extensive discussions and advancements in understanding spatial interactions through human mobility, most of the existing studies focused on aggregated flows without semantic differentiation, or on specific types of flows, such as commuting flow (Kung et al. 2014; Xie et al. 2025) and tourist flow (Liu et al. 2023). In other words, the heterogeneity of spatial patterns and the governing laws underlying different human behaviors in urban spaces remain relatively underexplored.

To address this gap, we propose the concept of **behavioral spatial interactions**, defined as collective flow patterns themed by the different activity types of individual trips. Leveraging large-scale mobile positioning data, we extract individual activity-labeled trips, aggregate them as themed origin–destination (OD) flows to uncover stratified patterns of behavioral spatial interactions. For preliminary results, we mapped the flow patterns of these behavioral spatial interactions, along with their detected community structures and calibrated distance-decay relationships. The results verify the classic disciplines while revealing heterogeneity across behavior-specific flows in metropolitan areas, highlighting the significance of distinguishing activity types associated with daily travel in urban transportation management and planning.

Data and Method

The raw data utilized in this project was collected from PlaceIQ as an anonymized, privacy-protected individual-level mobile-phone positioning dataset (Precisely 2024). Our collected whole dataset encompasses the entire United States and represents approximately 5% of the U.S. population, with each record including a unique device ID, timestamp, coordinates (in longitude-latitude format), stay duration of the user, and other information. For this project, we selected the period in the month of July, 2021 and extracted 52,898,950 individual trips for the seven-county area of Chicago (Chicago MSA) for further data processing, flow visualization, and network analysis.

Flow visualization

We implement a three-step workflow to extract individual trips labeled by daily activities, aggregate labeled trips at the Census Block Group (CBG) level, and map the behavioral spatial interactions:

- Coarse classification for home and work detection: A machine-learning-based framework was developed to identify home and work locations, two primary daily activity locations, associated with individual visitations (Song et al. 2025).
- POI-augmented secondary activity inference: We further infer activity types associated with records not labeled as home or work by incorporating external Points of Interest (POI) data from Foursquare Open Source Places (Foursquare 2024). A nearest-neighbor search (Abbasifard et al. 2014) is conducted to assign a valid activity label for the selected records.
- Trip and flow aggregation: Finally, we arrange the fine-labeled records for each individual in chronological order and extracted trips with both origin (O) and destination (D) labeled as home, work, or other activity types inferred from POIs, including Business & Professional Services, Retail, Dining & Drinking, Travel & Transportation, Landmarks & Outdoors, Arts & Entertainment, Health & Medicine, and Community & Government. These activity-labeled individual trips are aggregated into themed OD flows at the CBG level for further visualization, network analysis, and spatial interaction modeling.

Network analysis

We fit the behavioral flow intensities to the gravity model (Zipf 1946) to quantify the heterogeneity of the distance decay effect for different behavioral interactions. The regression is conducted via a log-linear gravity specification:

$$\ln\left(T_{ij}^{k}\right) = \beta_0 + \beta_1 \ln(P_i) + \beta_2 \ln\left(A_j^{k}\right) + \beta_3 \ln\left(d_{ij}\right) + \varepsilon_{ij}$$

where T_{ij}^{k} is the flow observed from the origin CBG i to the destination CBG j for the activity label k; P_i is the residential population of the origin CBG; A_j^{k} is the count of

POIs of activity type k in the destination CBG j, which serves as a measure of the destination attractiveness; and d_{ij} is the Euclidean distance (km) between CBG centroids, computed in UTM Zone 15N. The coefficients β_1, β_2, and β_3 are interpreted as elasticities: β_1 and β_2 capture the proportional change in flow associated with a one-percent increase in origin population and destination POI count, respectively, while β_3 represents the distance decay elasticity as expressed by the log-log transformation. We estimate Equation separately for each activity, as well as in a pooled specification that includes purpose-specific fixed effects. Intrazonal pairs ($i = j$) and observations with zero flow, population, or POI count are excluded.

Beyond overall spatial interaction characteristics, we apply community detection algorithms to investigate the commonalities and differences in the behavioral spatial interactions. Given the flow aggregated from individual trips, we constructed the spatial network, where nodes represent the CBG and edges are weighted by flow volume. Using the Louvain method (Blondel et al. 2008), we partitioned the spatial network into communities where nodes exhibit denser internal connections compared to their external links, highlighting the geographic boundaries of behavior-specific travel.

Results

The distance decay of different behavioral spatial interactions exhibits heterogeneity according to log-linear gravity modeling results (Table 1). Flows of Business & Professional Services ($\hat{\beta}_3$=−0.674), Retail ($\hat{\beta}_3$=−0.635), and Dining & Drinking ($\hat{\beta}_3$=−0.595) are more sensitive to distance increases than other types of flows, reflecting the local preference of these common daily activities in human mobility. These three types of behavioral flows are also more sensitive to the increase of origin population or destination POI (the largest $\hat{\beta}_1$ and $\hat{\beta}_2$), as these behaviors can be better characterized by supply–demand relationships. In contrast, the flows of Arts & Entertainment are the least sensitive to the increase in distance ($\hat{\beta}_3 = -0.383$), indicating a greater willingness to travel longer distances for museums and famous landmarks.

Purpose	N	$\hat{\beta}_1$ (ln_O)	$\hat{\beta}_2$ (ln_D)	$\hat{\beta}_3$ (ln_dist)	R^2	DW
Business & Prof. Services	1,840,000	0.286^{***}	0.273^{***}	-0.674^{***}	0.345	1.138
Retail	1,329,084	0.281^{***}	0.292^{***}	-0.635^{***}	0.327	1.232
Dining & Drinking	1,383,155	0.287^{***}	0.227^{***}	-0.595^{***}	0.300	1.201
Travel & Transportation	1,118,318	0.268^{***}	0.185^{***}	-0.523^{***}	0.281	1.274
Landmarks & Outdoors	718,115	0.236^{***}	0.213^{***}	-0.480^{***}	0.279	1.397
Arts & Entertainment	407,546	0.225^{***}	0.125^{***}	-0.383^{***}	0.226	1.469
Health & Medicine	664,191	0.269^{***}	0.187^{***}	-0.536^{***}	0.287	1.325
Community & Government	931,082	0.246^{***}	0.171^{***}	-0.506^{***}	0.303	1.275
Pooled	8,835,036	0.268^{***}	0.221^{***}	-0.563^{***}	0.302	1.244

Notes: The pooled model additionally includes activity-type fixed effects. DW = Durbin–Watson statistic, a statistic to test for spatial autocorrelation. ***, $p < 0.001$.

Table 1: OLS gravity model fitting by trip activity type — Chicago MSA.

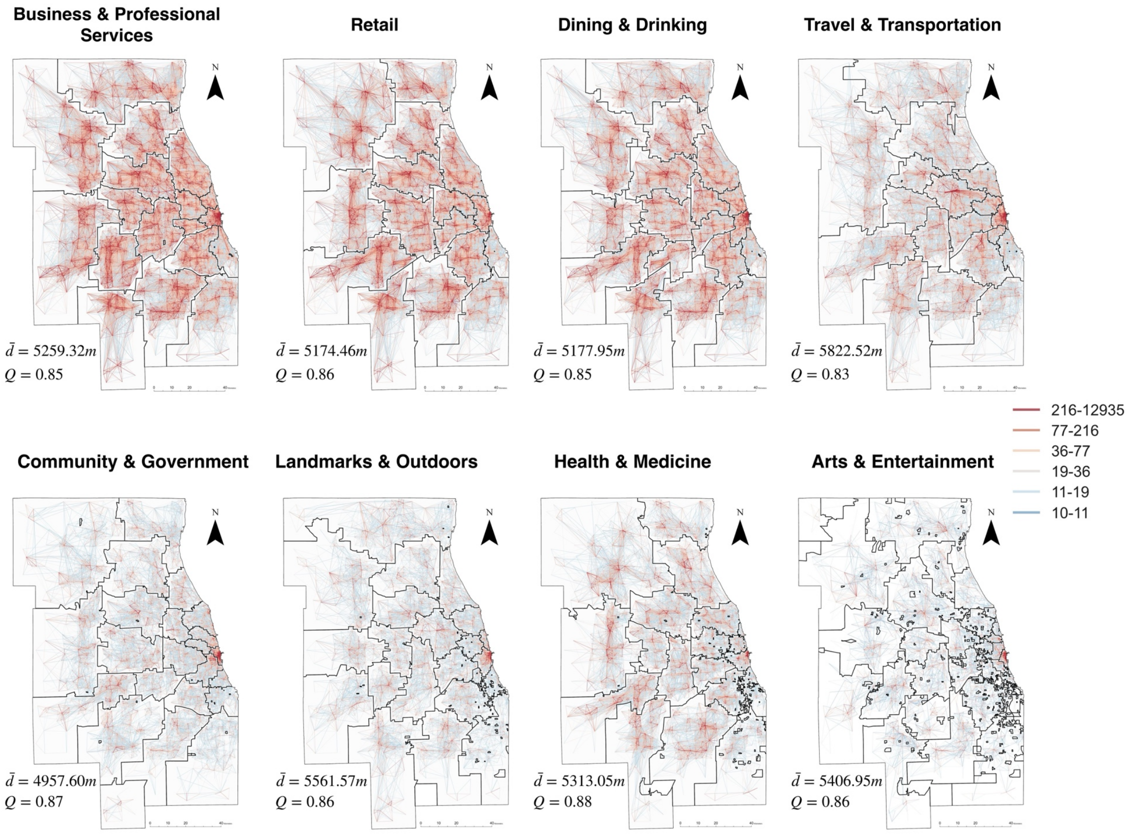

Figure 1: Eight behavioral spatial interaction patterns in the Chicago MSA with their detected community boundaries. For each map, $\bar{d}$ represents the average distance of flows, and Q represents the modularity. Flow volumes are represented by a unified color scheme; the class intervals were determined using natural breaks on the Business and Professional services flow, which contains the highest flow volume, and applied uniformly to all other maps.

We further visualize the intra-community flow patterns of eight behavioral spatial interactions by Louvain method to illustrate their mesoscopic network structures (Figure 1). Overall, the networks of Business & Professional Services, Retail, and Dining & Drinking exhibit higher densities and shorter average flow distances across the metropolitan area than the others, indicating both higher visitation frequencies and a polycentric distribution of these everyday services. The rest of the behavioral flows show lower network densities as well as more monocentric patterns centered on the downtown area. Compared to flows related to Health & Medicine and Community & Government, those associated with Landmarks & Outdoors and Arts & Entertainment exhibit more significant monocentric patterns and longer average flow distances. Such discoveries are consistent with the distance-decay coefficients shown in Table 1, reflecting the spatial concentration of recreational and tourism resources in the urban space. Despite overall discrepancies, the community structures of Retail and Dining & Drinking are similar to each other, while those of Business & Professional Services and Community & Government also exhibit close resemblance. The former pair aligns with observed flow patterns, while the latter suggests that similar modularity characteristics can be found in networks with varying densities.

Discussion and Conclusion

In this study, we propose to disentangle the comprehensive human mobility network into behavioral spatial interactions that reflect collective patterns of different activity types of individual trips. By mapping and analyzing diverse behavioral spatial interaction networks derived from large-scale mobile positioning data in Chicago, we highlight the stratified heterogeneity of behavioral spatial interactions in terms of network structures and distance decay functions. Our findings demonstrate the multi-layer behavioral heterogeneity within urban mobility flows and highlight the great potential to further investigate such intrinsic complexity of mobility networks. Future work will conduct more detailed statistical comparisons of activity types associated with trip origins and examine the consistency and variation of these patterns across multiple regions.

Acknowledgements:

This work is funded by the McKnight Land-Grant Professorship Award at University of Minnesota, the Grant-in-aid (GIA) of Research, Artistry, and Scholarship program in University of Minnesota, and the CTS Seed Fund, Minnesota Department of Transportation (CON000000106169).

References

Abbasifard, M. R., Ghahremani, B., & Naderi, H. (2014). A survey on nearest neighbor search methods. International Journal of Computer Applications, 95(25).

Andris, C., Koylu, C., & Porter, M. A. (2023). Human-network regions as effective geographic units for disease mitigation. EPJ Data Science, 12, 60. doi: 10.1140/epjds/s13688-023-00426-1

Belyi, A., Bojic, I., Sobolevsky, S., et al. (2017). Global multi-layer network of human mobility. International Journal of Geographical Information Science, 31, 1381–1402. doi: 10.1080/13658816.2017.1301455

Blondel, V. D., Guillaume, J.-L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. Journal of Statistical Mechanics: Theory and Experiment, 2008, P10008. doi: 10.1088/1742-5468/2008/10/P10008

Foursquare. (2024). Foursquare Open Source Places. https://opensource.foursquare.com/os-places/

Guo, D. (2009). Flow mapping and multivariate visualization of large spatial interaction data. IEEE Transactions on Visualization and Computer Graphics, 15, 1041–1048. doi: 10.1109/TVCG.2009.143

Im, J., & Ko, J. (2026). Investigating the spatiotemporal variability of mobility-based centrality in Seoul using mobile phone signaling data. Journal of Transport Geography, 132, 104603. doi: 10.1016/j.jtrangeo.2026.104603

Ioannou, G., Pallis, G., Dikaiakos, M., & Nicolaides, C. (2025). Utilizing large-scale human mobility data to identify determinants of physical activity. Scientific Reports, 15, 3420. doi: 10.1038/s41598-025-87017-4

Koylu, C., & Guo, D. (2017). Design and evaluation of line symbolizations for origin–destination flow maps. Information Visualization, 16, 309–331. doi: 10.1177/1473871616681375

Koylu, C., Guo, D., Huang, Y., Kasakoff, A., & Grieve, J. (2021). Connecting family trees to construct a population-scale and longitudinal geo-social network for the US. International Journal of Geographical Information Science, 35, 2380–2423. doi: 10.1080/13658816.2020.1821885

Kung, K. S., Greco, K., Sobolevsky, S., & Ratti, C. (2014). Exploring universal patterns in human home-work commuting from mobile phone data. PLOS ONE, 9, e96180. doi: 10.1371/journal.pone.0096180

Liu, S., Zhang, J., Liu, P., Xu, Y., Xu, L., & Zhang, H. (2023). Discovering spatial patterns of tourist flow with multi-layer transport networks. Tourism Geographies, 25, 113–135. doi: 10.1080/14616688.2020.1850849

Liu, Y., Liu, X., Gao, S., et al. (2015). Social sensing: A new approach to understanding our socioeconomic environments. Annals of the Association of American Geographers, 105, 512–530. doi: 0.1080/00045608.2015.1018773

Mokhtarian, P. L., & Salomon, I. (2001). How derived is the demand for travel? Some conceptual and measurement considerations. Transportation Research Part A: Policy and Practice, 35, 695–719. doi: 10.1016/S0965-8564(00)00013-6

Nilforoshan, H., Looi, W., Pierson, E., et al. (2023). Human mobility networks reveal increased segregation in large cities. Nature, 624, 586–592. doi: 10.1038/s41586-023-06757-3

Pappalardo, L., Manley, E., Sekara, V., & Alessandretti, L. (2023). Future directions in human mobility science. Nature Computational Science, 3, 588–600. doi: 10.1038/s43588-023-00469-4

Precisely. (2024). Precisely Places (formerly PlaceIQ). https://www.precisely.com/product/precisely-places/

Schläpfer, M., Dong, L., O'Keeffe, K., et al. (2021). The universal visitation law of human mobility. Nature, 593, 522–527. doi: 10.1038/s41586-021-03480-9

Song, Y., Xiong, M., Zeng, X., & Zhu, D. (2025). A behavior-informed and geo-context-aware home detection framework for mobile phone positioning data. Proceedings of the 33rd ACM International Conference on Advances in Geographic Information Systems, 1008–1018. doi: 0.1145/3748636.3764171

Šveda, M., & Sládeková Madajová, M. (2023). Estimating distance decay of intra-urban trips using mobile phone data: The case of Bratislava, Slovakia. Journal of Transport Geography, 107, 103552. doi: 10.1016/j.jtrangeo.2023.103552

Tang, J., Liu, F., Wang, Y., & Wang, H. (2015). Uncovering urban human mobility from large scale taxi GPS data. Physica A: Statistical Mechanics and Its Applications, 438, 140–153. doi: 10.1016/j.physa.2015.06.032

Verma, R., & Ukkusuri, S. V. (2025). What determines travel time and distance decay in spatial interaction and accessibility? Journal of Transport Geography, 122, 104061. doi: 10.1016/j.jtrangeo.2024.104061

Welch, T. F., & Widita, A. (2019). Big data in public transportation: A review of sources and methods. Transport Reviews, 39, 795–818. doi: 10.1080/01441647.2019.1616849

Wheeler, J. O. (1972). Trip purposes and urban activity linkages. Annals of the Association of American Geographers, 62, 641–654. doi: 10.1111/j.1467-8306.1972.tb00892.x

Wilson, A. G. (1971). A family of spatial interaction models, and associated developments. Environment and Planning A, 3, 1–32. doi: 10.1068/a030001

Xie, Z., Huang, B., Cai, J., & Lee, H. F. (2025). Commuting flow patterns across a triad of Chinese megacities: Evidence from Poisson gravity modeling using mobile device data. Journal of Transport Geography, 128, 104380. doi: 10.1016/j.jtrangeo.2025.104380

Xu, F., Wang, Q., Moro, E., et al. (2025). Using human mobility data to quantify experienced urban inequalities. Nature Human Behaviour, 9, 654–664. doi: 10.1038/s41562-024-02079-0

Yang, X., Fang, Z., Xu, Y., Yin, L., Li, J., & Lu, S. (2019). Spatial heterogeneity in spatial interaction of human movements—Insights from large-scale mobile positioning data. Journal of Transport Geography, 78, 29–40. doi: 10.1016/j.jtrangeo.2019.05.010

Zhu, D., Ye, X., & Manson, S. (2021). Revealing the spatial shifting pattern of COVID-19 pandemic in the United States. Scientific Reports, 11, 8396. doi: 10.1038/s41598-021-87902-8

Zipf, G. K. (1946). The P_1P_2/D hypothesis: On the intercity movement of persons. American Sociological Review, 11, 677–686. doi: 0.2307/2087063