A REVIEW OF URBAN HUMAN MOBILITY RESEARCH BASED ON CROWD-SOURCED DATA AND SPACE-TIME AND SEMANTIC ANALYSIS

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ABSTRACT:

Detecting urban human mobility patterns helps contributes to many urbanization issues, such as urban planning and traffic management. With the growing volume of crowd-sourced data, many studies have benefited from this data type to explore people's daily movements and track their activities. There are several published review papers examing these studies on urban human mobility, with the focus on defining models and applications. However, the absence of a review of studies on urban human mobility that considered spatial, temporal, and semantic properties as well as crowd-sourced data together has limited the proliferation of semantic content in addressing mobility issues. In response, this paper provides a review on urban human mobility, including the data, models, and applications used in the selected articles. We defined particular inclusion and exclusion criteria to select the most relevant articles. We also included metadata analysis to overview the existing relevant literature. Finally, several research challenges and open issues are discussed.

1. INTRODUCTION

Urban human mobility pertains to people's movement on a city-wide scale (Zhou et al., 2018). Understanding human mobility is crucial for several purposes and applications, such as urban planning (Yuan et al., 2012; Qi et al., 2011), transportation planning, and traffic forecasting (Goh et al., 2012; Huang et al., 2019). Most of the existing literature reviews focus on understanding urban human mobility with an emphasis on geospatial and spatiotemporal analyses (Abbasi et al., 2017; Rashidi et al., 2017) via social media and big data (Luo et al., 2016; Chaniotakis et al., 2017). However, the motivation behind the mobility patterns, reflected by the semantic information (Huang and Li, 2016), is overlooked. Some existing studies have studied textual context in social media data for human activity modeling. However, they still do not take a comprehensive look at the semantic content of mobility issues. Therefore, it is critical to integrate spatial-temporal data with semantic information by utilizing social media data more effectively and comprehensively (Liu et al., 2021).

We concentrated our review work on papers using crowd-sourced data to study human mobility. This type of data is usually collected by volunteer users and can be cost-effective (Niu and Silva, 2020).

There are several review papers on human mobility, with their primary focus on defining models and applications (Barbosa et al., 2018), data mining (Niu & Silva, 2020; Zhao et al., 2016), big data and smart cities (Wang et al., 2021), machine learning methods (Toch et al., 2019), deep learning methods (Luca et al., 2021), and mobility in COVID-19 (Benita, 2021). However, to the best of our knowledge, no review has been done exploring all three aspects, i.e., spatial, temporal, and semantic, simultaneously using crowd-sourced data. Our study includes the peer-reviewed papers indexed on the Web of Science and Scopus. The remainder of the article is organized as follows. Section 2 describes the paper selection procedure of this study as well as inclusion and exclusion criteria. The third section presents the meta-analysis of the reviewed articles to provide an overall perspective of the literature on the studied theme. The data and models used in the reviewed studies are further explored in Sections 4 and 5 accordingly, followed by a brief discussion on some applications in Section 6 and some concluding remarks in the final section.

2. PAPER SELECTION

This study aims to locate relevant literature based on particular inclusion and exclusion criteria. Figure 1 shows the PRISMA process of the article selection. After this process, 28 papers were selected following our search through the two databases, Web of Science and Scopus. We created a search query, which is a list of critical concepts encompassing urban human mobility, spatial-temporal-semantic properties, and crowd-sourced data. These concepts were combined with Boolean operators to execute a search in the defined databases (see Table 1).

(urban OR city OR cities) AND ("human activit*" OR "human mobilit*" OR "human movement") AND (space OR spatial OR geospatial OR geographical OR geography OR spatio-temporal OR spatiotemporal OR spatial-temporal OR time OR temporal) AND (semantic* OR "geo semantic*" OR "geospatial semantic*" OR motivation* OR motiv* OR purpose*) AND ("crowd*sourc*" OR "crowd sens*" OR "social media" OR "social network*" OR POI* OR "point* of interest*" OR VGI OR "volunteered geographic information" OR "location based services" OR LBS OR "location-based social network" OR LBSN OR "location based social media"

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OR "LBSM" OR "user* generated content" OR geotagged OR Twitter OR tweet* OR Foursquare OR Flickr OR geo-data OR check-in*).

Table 1. The Query string in the database search engine.

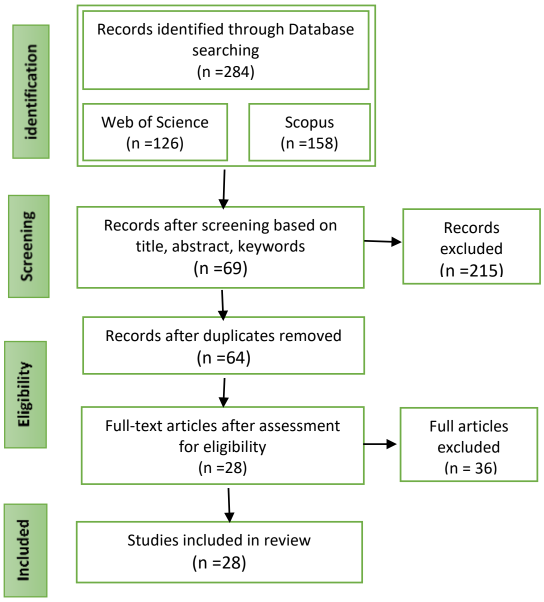

Figure 1. PRISMA diagram of the article selection process.

The search was limited to papers written in English and published in peer-reviewed journals or conference proceedings. Further, no limit or filter was selected regarding the publication date until 30 March 2022.

2.1. Inclusion criteria

The following studies were included:
1. Papers that use crowd-sourced data as the only data source or as the primary dataset together with other types of data
2. All three aspects of mobility data, including semantic, spatial, and temporal, are included and studied simultaneously
3. The scale of the included studies is intra-urban
4. Studies that deal with human movement and activities
5. Journal or conference papers that are peer-reviewed

2.2 Exclusion criteria:

The following studies were excluded:
1. If the primary dataset is not crowd-sourced, such as a research work conducted by using call detail record (CDR), or census data, that is not produced by the crowd.
2. If a study fails to consider spatial, temporal, and semantic properties together. In other words, only spatial-temporal or spatial or temporal aspects of human mobility are explored or just textual data regarding mobility issues are extracted.
3. If the mobility study scale is not urban, such as migrant mobility among cities, countries, or continents.

We evaluated the applied data and methods in the selected papers and reviewed their proposed applications and existing challenges.

3. META-ANALYSIS

Although several related articles were published in previous years, a considerable interest in studying urban human mobility with a focus on space-time and semantic properties and by applying crowd-sourced data started in 2015 (see Figure 2).

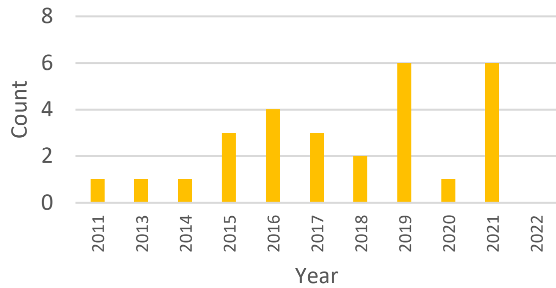

Figure 2. The number of included papers by year.

In terms of scientific disciplines, we analyzed the journals that have published the selected studies and classified them based on the journal category (see Figure 3). Most selected papers are published in computer science, geography, urban studies, and engineering journals.

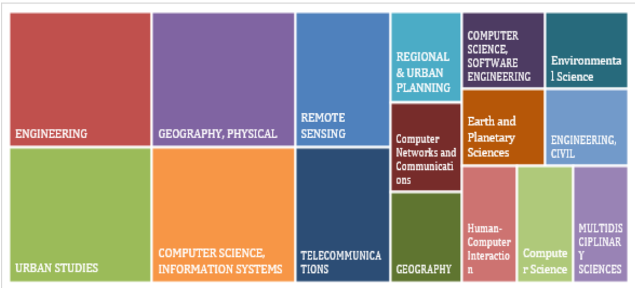

Figure 3. Treemap visualization of journal categories for papers.

In terms of the study area, the sample datasets used in half of the reviewed papers are from the USA and China, followed by Canada as the third dominant study area among selected papers (see Figure 4).

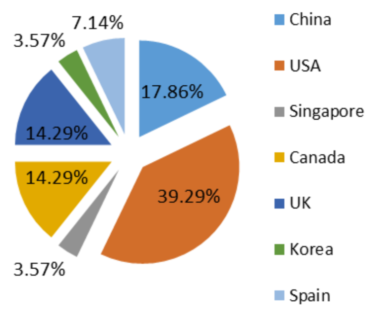

Figure 4. The number of papers by country.

Exploring the selected papers, it is inferable that the data availability significantly affects the selection of the study areas. For example, a study (Sari Aslam et al., 2021) selected London, one of the world's comprehensive public transport networks, as its study area. So, they used the smart card data provided by Transport for London (TfL) in developing their mobility model. Further, socio-economic profiles can also impact the study area selection in research. In other words, how easily users have access to the technology and can generate their data and make it available to others can influence the choice of the study area.

4. DATA

All the articles selected in this study have used crowd-sourced data as their primary data source. For example, Twitter in (Huang et al., 2016) and (Soliman et al., 2015), Foursquare in (Han and Yamana, 2016), Tencent in (Cai et al., 2019), and Sina Weibo in (Liu et al., 2021) are sample social media platforms used in the selected studies. These social media platforms provide data sets and metadata, such as spatial, temporal, and semantic information. These features contribute to understanding human mobility patterns and next location prediction. Points of Interest (POI), another popular data source, is characterized by location, contextual information and place or activity-categorization (Rossi et al., 2020), such as public areas, transportation, and recreation centers.

Twitter, Foursquare, and POIs were among frequently used datasets in the studied papers (see Figure 5). Jin & Claramunt (2018) and Cao et al. (2019) used GPS trajectory and POI data for studying human movement. The GPS data source for the former work was collected by the Geolife project, while the experimental dataset for the latter study was actual taxi trajectory data.

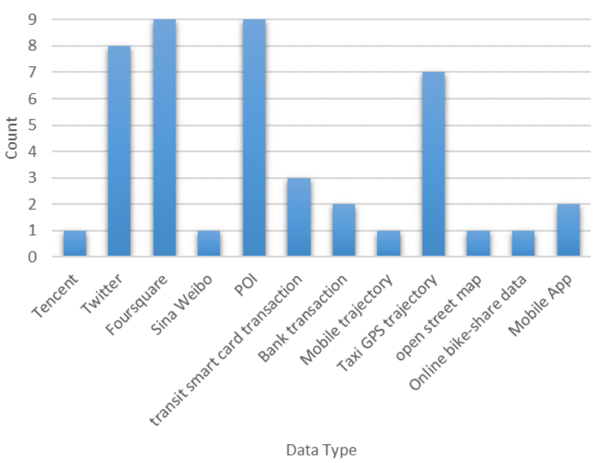

Figure 5. Dataset used in selected articles

Individual users can post data to collaborative websites, such as OpenStreetMap or online bike-share database maps (Dashdorj et al., 2014; Lee et al., 2021) according to specific policies.

Dashdorj et al. (2014) used OpenStreetMap and Points of Interest (POIs) to develop and validate his model of studying human mobility behavior. A country-wide bank card transaction data was applied to provide the POI data. This dataset includes semantic information about activity categories and spatial and temporal information.

In a study by (Huang and Li, 2019), they used Twitter data posted in Toronto, Canada, to extract spatiotemporal and semantic patterns of users to compare their activity patterns and explore the motivation behind the mobility patterns.

In another study, (Rossi et al., 2020) used GPS trace of the taxi trajectories. They provided semantic representation of the trajectory data from Foursquare.

Social media data like Twitter and Weibo have word limits and might not be adequate for semantic data analysis. Thus, social media data and data from taxicabs need to be enriched semantically (Toch et al., 2019) to provide comprehensive data for studying mobility patterns.

In terms of mobility data integration as a whole, there are some challenges. Since the spatial, temporal, and semantic properties of mobility data belong to different domains, their representation will be distinct.

Data Sparsity is another issue for fine-grained mobility patterns analysis. Some studies have presented new methods to tackle this data problem. For example, Shi et al. (2021) presented a von Mises-Fisher mixture clustering to alleviate pattern detection for groups with similar mobility patterns.

5. MODELING

The reviewed papers applied various models for identifying and predicting human mobility patterns at the city scale. The used methods include rule-based, statistical, and machine learning models. Rule-based models are the most traditionally employed method; however, statistical or machine learning models are frequently used in recent studies (Ermagun et al., 2017). The frequency of applied techniques in the reviewed papers also demonstrates the prevalence of machine learning (ML) models (see Figure 6 and). Statistical approaches use logistic models to classify the mobility types or trip purposes, while rule-based models use a set of formulas to detect the mobility patterns (Toch et al., 2019).

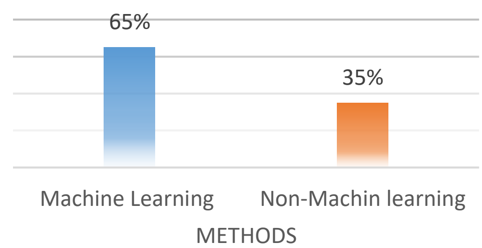

Figure 6. Frequency of applied methods

In the current literature review, topic modeling is one of the frequently used models by the selected papers. Topic modeling algorithms extract latent semantics in documents and create topics for classified themes (Kherwa and Bansal, 2020).

In a study done by (Wang et al. 2017), a hierarchical topic model was used to spot the trip purposes and simultaneously define the arrival events in a place.

Another study (Huang and Li, 2016) used topic modeling- LDA to develop a new model. This model quantitatively extracted human activity patterns based on specific spatiotemporal and semantic characteristics. According to their result, there might be different motivations behind similar mobility patterns. Latent Dirichlet Allocation (LDA) as one of the popular topic models does not consider the inner spatial correlations.

The neural network approach can be a good alternative when traditional methods such as the probabilistic model often struggle to extract complex sequential mobility patterns (Luca et al., 2021).

A study by (Rossi et al., 2020) demonstrated a significant improvement in the prediction accuracy of the next taxi drop-off location through the recurrent neural network approach.

Studied papers have employed multiple methods in exploring mobility issues, including machine learning and non-machine learning methods. For example, (Liu et al., 2021) integrated natural language processing, statistical and spatial analysis into a framework to study user mobility. They applied the Bidirectional Encoder Representations from Transformers (BERT) model (released by Google in 2018) to identify the semantic properties of human activity. BERT is a language encoder that changes the input text into corresponding semantic features (Devlin et al., 2019). The result showed more than 90% accuracy in daily activity pattern recognition.

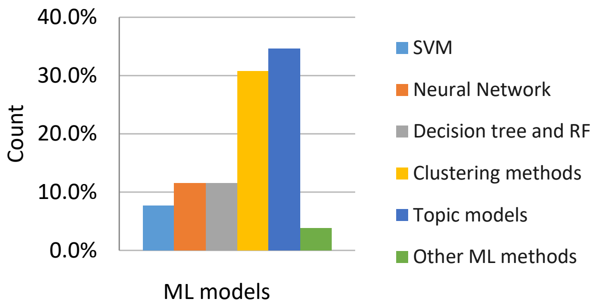

Figure 7. Frequency of used ML models in the reviewed studies.

Another paper (Wang et al., 2017) developed a joint model that integrates the Mixture of Hawkes Process (MHP) with a hierarchical topic model to capture the arrival sequences with mixed trip purposes.

Steiger et al. (2016) applied the Topic model (e.g., LDA) and Geo-H-SOM algorithm for detecting semantic similarity of tweets and spatiotemporal clusters of urban activity. Their work showed that the LDA method produced significantly better results than arbitrary keyword filtering models or word frequency-based techniques.

Some papers compared different classification methods; for example, (Zhu, 2021) employed a big training data set to evaluate the Random Forest (RF) model and the linear chain Conditional random fields (CRFs) model for activity classification. The results showed that the CRFs models have better sensitivity rates than RF models for most activity types due to the inclusion of Markovian transitions among activities.

In studying human mobility patterns, multi-view models perform better than single-view models. Multi-view human mobility models can integrate various single views and explore the mobility patterns comprehensively (Zhang et al., 2016).

(Shi et al., 2021) used multimodal embedding to work with high-dimensional datasets. The hidden Markov model was developed to learn latent states. They proposed a von Mises-Fisher mixture clustering for classifying users with similar mobility patterns to address mobility data sparsity issues. The used embedding methods improved the prediction accuracy and increased the training speed.

Considering the high-dimensional features of mobility data, another review paper (Niu and Silva, 2020) offered deep learning models rather than conventional topic modeling.

6. APPLICATIONS

The reviewed papers have presented many urban applications for human mobility studies. Reviewing the applications, we found that most human mobility analyses included predicting the crowd dynamics and detecting mobility patterns in urban studies as well as traffic control and modeling trip purposes.

Next location prediction is a well-studied application of human mobility. The prediction result can affect traffic congestion and optimize the performance of the electronic dispatching systems. Abideen et al. (2021) developed a model to predict taxi driver behavior. Urban planners apply similar models to plan traffic in the city and improve taxi company services because it can reduce the waiting time for the passengers and the driver.

Understanding urban human mobility is crucial for transportation, urban planning, and policymaking. Huang et al. (2019) used geotagged tweets to explore the effect of human activities on daily traffic. They applied DBSCAN-based clustering for spatiotemporal analysis and used LDA (Latent Dirichlet allocation) to infer the semantics in each cluster

7. CONCLUSIONS

We surveyed existing studies on urban human mobility regarding data, mobility models, and applications. In this study, existing papers that apply crowd-sourced data to study the spatial, temporal, and semantic aspects of human mobility on an urban scale were systematically analyzed through a meta-analysis. Based on the inclusion and exclusion criteria, 28 papers were selected for detailed review.

Our overview of the human mobility studies identifies some of the challenges and corresponding future directions described in the following.

Twitter data cannot produce an accurate, unbiased representation of human activities as a dominant crowd-sourced data. Data fusion is needed to integrate various data sources, such as point-of-interest data and other georeferenced documents (Fu et al., 2018). Further, to solve the heterogeneity problem of the land use, POI data enriches the semantic data, including visual and textual information about the check-ins.

In terms of geographic transferability, it is necessary to investigate whether the applied methods can provide a similar degree of accuracy when used in other study areas and cities. Machine learning and deep learning methods, for example, are highly dependent on the training dataset, and results based on the training dataset might not be transferrable to another location and cannot always be generalized or will not lead to reliable and robust conclusions.

Compared to the overall population, social media users have problems regarding representation and sampling (Huang and Li, 2019). However, datasets can be enriched by integrating multiple

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data types and data sources to increase the overall reliability of the analysis results.

Conventional methods cannot effectively capture all the factors for human mobility modeling, including the relations between users, time, space, and semantic properties(Shi et al., 2021). Deep learning (DL) techniques can have better performance, but the Black-Box nature of DL models leads to poor interpretability and explainability. This issue with the DL models may be tackled by knowledge-infused learning, such as a knowledge graph(Gaur et al., 2021).

Considering heterogeneity in data, specific models such as the graph embedding method (Shi et al., 2021) can include semantics in the model and improve the task accuracy. Also, in-depth mining of social text data efficiently identifies text information types and hidden content. Applying natural language processing models such as the BERT model produces highly reliable text multiclassification and semantic data analysis results.

Regarding the massive and high dimensional crowd-sourced data and diversity in the methods and applications in urban human mobility, there is still a large room to improve the field, especially involving crowd-sourced data and semantic information.

REFERENCES

Abbasi, O.R., Alesheikh, A., Sharif, M., 2017. Ranking the City: The Role of Location-Based Social Media Check-Ins in Collective Human Mobility Prediction. Int. J. Geo-Information 6, 136. https://doi.org/10.3390/ijgi6050136

Abideen, Z., Sun, H.L., Yang, Z., Ahmad, R.Z., Iftekhar, A., Ali, A., 2021. Deep Wide Spatial-Temporal Based Transformer Networks Modeling for the Next Destination According to the Taxi Driver Behavior Prediction. Appl. Sci. 11. https://doi.org/10.3390/app11010017

Barbosa, H., Barthelemy, M., Ghoshal, G., James, C.R., Lenormand, M., Louail, T., Menezes, R., Ramasco, J.J., Simini, F., Tomasini, M., 2018. Human mobility: Models and applications. Phys. Rep. 734, 1–74. https://doi.org/https://doi.org/10.1016/j.physrep.2018.01.001

Benita, F., 2021. Human mobility behavior in COVID-19: A systematic literature review and bibliometric analysis. Sustain. Cities Soc. 70, 102916. https://doi.org/https://doi.org/10.1016/j.scs.2021.102916

Cai, L., Xu, J., Liu, J., Ma, T., Pei, T., Zhou, C., 2019. Sensing multiple semantics of urban space from crowdsourcing positioning data. Cities 93, 31–42. https://doi.org/10.1016/j.cities.2019.04.011

Cao, N., Li, S.F., Shen, K.Y., Bin, S., Sun, G.X., Zhu, D.J., Han, X.L., Cao, G.S., Campbell, A., 2019. Semantics Analytics of Origin-Destination Flows from Crowd Sensed Big Data. C. Mater. Contin. 61, 227–241. https://doi.org/10.32604/cmc.2019.06125

Chaniotakis, E., Antoniou, C., Aifadopoulou, G., Dimitriou, L., 2017. Inferring Activities from Social Media Data. Transp. Res. Rec. 2666, 29–37. https://doi.org/10.3141/2666-04

Dashdorj, Z., Sobolevsky, S., Serafini, L., Ratti, C., 2014. Human activity recognition from spatial data sources, Proceedings of the Third Acm Sigspatial International Workshop on Mobile Geographic Information Systems. https://doi.org/10.1145/2675316.2675321

Devlin, J., Chang, M.-W., Lee, K., Toutanova, K., 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding, in: NAACL.

Ermagun, A., Fan, Y., Wolfson, J., Adomavicius, G., Das, K., 2017. Real-time trip purpose prediction using online location-based search and discovery services. Transp. Res. Part C Emerg. Technol. 77, 96–112. https://doi.org/10.1016/j.trc.2017.01.020

Gaur, M., Faldu, K., Sheth, A., 2021. Semantics of the Black-Box: Can Knowledge Graphs Help Make Deep Learning Systems More Interpretable and Explainable? IEEE Internet Comput. 25, 51–59. https://doi.org/10.1109/MIC.2020.3031769

Goh, S., Lee, K., Park, J., CHOI, M., 2012. Modification of the gravity model and application to the metropolitan Seoul subway system. Phys. Rev. E 86. https://doi.org/10.1103/PhysRevE.86.026102

Han, J., Yamana, H., 2016. A study on individual mobility patterns based on individuals' familiarity to visited areas. Int. J. Pervasive Comput. Commun. 12, 23–48. https://doi.org/10.1108/IJPCC-01-2016-0010

Huang, W., Li, S., 2019. An approach for understanding human activity patterns with the motivations behind. Int. J. Geogr. Inf. Sci. 33, 385–407. https://doi.org/10.1080/13658816.2018.1530354

Huang, W., Li, S., 2016. Understanding human activity patterns based on space-time-semantics. ISPRS J. Photogramm. Remote Sens. 121, 1–10. https://doi.org/https://doi.org/10.1016/j.isprsjprs.2016.08.008

Huang, W., Li, S., Xu, S., 2016. A three-step spatial-temporal-semantic clustering method for human activity pattern analysis. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. 41, 549.

Huang, W., Xu, S.S., Yan, Y.W., Zipf, A., 2019. An exploration of the interaction between urban human activities and daily traffic conditions: A case study of Toronto, Canada. Cities 84, 8–22. https://doi.org/10.1016/j.cities.2018.07.001

Jin, M.H., Claramunt, C., 2018. A Semantic Model for Human Mobility in an Urban Region. J. Data Semant. 7, 171–187. https://doi.org/10.1007/s13740-018-0092-4

Kherwa, P., Bansal, P., 2020. Topic Modeling: A Comprehensive Review. EAI Endorsed Trans. Scalable Inf. Syst. 7, e2.

Lee, J., Yu, K., Kim, J., 2021. Public bike trip purpose inference using point-of-interest data. ISPRS Int. J. Geo-Information 10. https://doi.org/10.3390/ijgi10050352

Liu, J., Meng, B., Wang, J., Chen, S.Y., Tian, B., Zhi, G.Q., 2021. Exploring the Spatiotemporal Patterns of Residents' Daily Activities Using Text-Based Social Media Data: A Case Study of Beijing, China. ISPRS Int. J. Geo-Information 10. https://doi.org/10.3390/ijgi10060389

Luca, M., Barlacchi, G., Lepri, B., Pappalardo, L., 2021. A Survey on Deep Learning for Human Mobility. ACM Comput. Surv. 55. https://doi.org/10.1145/3485125

Luo, F., Cao, G., Muligan, K., Li, X., 2016. Explore spatiotemporal and demographic characteristics of human mobility via Twitter: A case study of Chicago. Appl. Geogr. 70, 11–25. https://doi.org/https://doi.org/10.1016/j.apgeog.2016.03.001

Niu, H., Silva, E.A., 2020. Crowdsourced Data Mining for Urban Activity: Review of Data Sources, Applications, and Methods. J. Urban Plan. Dev. 146, 15. https://doi.org/10.1061/(asce)up.1943-5444.0000566

Qi, G., Li, X., Li, S., Pan, G., Wang, Z., Zhang, D., 2011. Measuring social functions of city regions from large-scale taxi behaviors, in: 2011 IEEE International Conference on Pervasive Computing and Communications Workshops (PERCOM Workshops). pp. 384–388. https://doi.org/10.1109/PERCOMW.2011.5766912

Rashidi, T., Abbasi, A., Maghrebi, M., Hasan, S., Waller, T., 2017. Exploring the capacity of social media data for modelling travel behaviour: Opportunities and challenges. Transp. Res. Part C Emerg. Technol. 75, 197–211. https://doi.org/10.1016/j.trc.2016.12.008

Rossi, A., Barlacchi, G., Bianchini, M., Lepri, B., 2020. Modelling Taxi Drivers' Behaviour for the Next Destination Prediction. IEEE Trans. Intell. Transp. Syst. 21, 2980–2989. https://doi.org/10.1109/TITS.2019.2922002

Sari Aslam, N., Zhu, D., Cheng, T., Ibrahim, M.R., Zhang, Y., 2021. Semantic enrichment of secondary activities using smart card data and point of interests: a case study in London. Ann. GIS 27, 29–41. https://doi.org/10.1080/19475683.2020.1783359

Shi, H.Z., Li, Y., Cao, H.C., Zhou, X.X., Zhang, C., Kostakos, V., 2021. Semantics-Aware Hidden Markov Model for Human Mobility. IEEE Trans. Knowl. Data Eng. 33, 1183–1194. https://doi.org/10.1109/tkde.2019.2937296

Soliman, A., Padmanabhan, A., Yin, J., Soltani, K., Wang, S., 2015. Where Chicagoans tweet the most: Semantic analysis of preferential return locations of Twitter users, in: Proceedings of the 1st International ACM SIGSPATIAL Workshop on Smart Cities and Urban Analytics, UrbanGIS 2015. pp. 55–58. https://doi.org/10.1145/2835022.2835032

Steiger, E., Resch, B., Zipf, A., 2016. Exploration of spatiotemporal and semantic clusters of Twitter data using unsupervised neural networks. Int. J. Geogr. Inf. Sci. 30, 1694–1716. https://doi.org/10.1080/13658816.2015.1099658

Toch E., Lerner, B., Ben-Zion, E., Ben-Gal, I., 2019. Analyzing large-scale human mobility data: a survey of machine learning methods and applications. Knowl. Inf. Syst. 58, 501–523. https://doi.org/10.1007/s10115-018-1186-x

Wang, A., Zhang, A., Chan, E.H.W., Shi, W., Zhou, X., Liu, Z., 2021. A Review of Human Mobility Research Based on Big Data and Its Implication for Smart City Development. ISPRS Int. J. Geo-Information 10, 17. https://doi.org/10.3390/ijgi10010013

Wang, P., Fu, Y., Liu, G., Hu, W., Aggarwal, C., 2017. Human Mobility Synchronization and Trip Purpose Detection with Mixture of Hawkes Processes, Kdd'17: Proceedings of the 23rd Acm Sigkdd International Conference on Knowledge Discovery and Data Mining. Assoc Computing Machinery, New York. https://doi.org/10.1145/3097983.3098067

Yuan, J., Zheng, Y., Xie, X., 2012. Discovering regions of different functions in a city using human mobility and POIs, in: KDD.

Zhang, F., Zhu, X., Guo, W., Ye, X., Hu, T., Huang, L., 2016. Analyzing Urban Human Mobility Patterns through a Thematic Model at a Finer Scale. ISPRS Int. J. Geo-Information 5, 17. https://doi.org/10.3390/ijgi5060078

Zhao, K., Tarkoma, S., Liu, S., Vo, H., 2016. Urban Human Mobility Data Mining: An Overview, 2016 Ieee International Conference on Big Data. Ieee, New York.

Zhou, Y., Lau, B.P.L., Yuen, C., Tuncer, B., Wilhelm, E., 2018. Understanding urban human mobility through crowdsensed data. IEEE Commun. Mag. 56, 52–59.

Zhu, Y., 2021. Inference of activity patterns from urban sensing data using conditional random fields. Environ. Plan. B-Urban Anal. City Sci. https://doi.org/10.1177/23998083211016863