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Spatio-Temporal Understanding and Representation of Transformative Urban Mobility and Trip Patterns, A Review

Arian Behradfar[1] **and Soheil Mohammadi**[2]

[1]*Department of Geomatics and Spatial Information Engineering, College of Engineering, University of Tehran, Tehran 1439957131, Iran*
[2]*Department of Naval, Electrical, Electronic and Telecommunications Engineering, DITEN, University of Genoa, Genoa 16126, Italy*

Corresponding author's Email: arian.behradfar92@gmail.com

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ABSTRACT

The rapid development in transport system monitoring provide planners and researchers with new opportunities to understand the trends of mobility patterns in urban areas, known as transformation of urban mobility. It brings businesses and cities together to implement system-level integrated initiatives to conducting urban mobility and transport system toward a more efficient future. As a result, identification of the trip patterns and spatio-temporal dependencies in urban areas requires a comprehensive understanding of high-dimensional human mobility dynamics. These emerging trends need a framework to identify urban mobility patterns from a spatio-temporal perspective that includes various visualized representation of mobility patterns and travel behaviour. The main purpose of this study is to investigate different data sources and methods used in the literature to obtain the proposed patterns in urban areas. The spatio-temporal models evaluated in this review can be used in a wide range of mobility studies suggesting trip patterns and related variables are significantly affected by spatial and non-spatial impacts.

Keywords: Transformation of urban mobility, Mobility flows, Trip patterns, spatio-temporal dependencies, spatial analysis

INTRODUCTION

Mobility can be considered as an important socio-economic resource and articulator in society, since it is directly related to the movement of people between different spatio-temporal hierarchies. The rapid growth in urban areas, private vehicle fleet and the lack of proper planning of transportation systems have led to increasing deterioration of mobility, emerging different social challenges and environmental problems (Costa et al., 2017: Khanian et al., 2018).

Urban areas will require mobility solutions and changes that are sustainable, affordable, inclusive and integrated with people-centric infrastructure and services. These solutions rest on the transformation of urban mobility that includes a holistic and systemic approach that acts in the intersection between mobility infrastructure, social benefits, economic efficiency, and environmental impact. The transformation of urban mobility delivers a cohesive set of initiatives that act at the system level. Each co-designed action aims to remove barriers and mobilize stakeholders to contribute to transforming mobility (Hegyi et al., 2019).

The future of mobility represents opportunities for cities and planners to collaborate and accelerate the creation and deployment of sustainability. As a result, the identification of main individual aspects that provide vital information on the progress and effectiveness of mobility transformation is completely essential in transportation engineering. These individual aspects have to comprise various characteristics of interaction trends and precisely express mobility specifics in urban areas so that simultaneously take into account the three dimensions of sustainability: social, economic and environmental issues (Gheitarani et al., 2020: Bibri, 2019).

One of the best sources for monitoring the transformation of urban mobility is obtaining daily mobility patterns of an urban area. These regular mobility flows are reflected in different aspects of people's movement trajectory and transport system structure. Urban trips distribution, travel behavior, spatial interaction, activity identification, temporal dependencies, and trip pattern segments. This information can lead to understanding the current structure of urban mobility and existing trends and challenges in large-scale from a spatio-temporal perspective (Sun et al., 2016).

As we discussed, the main purpose of this study is to understand the trip patterns in urban areas based on travel behaviour analysis. Deriving the major characteristics of mobility system and the necessitate trends in different parts of the mobility strategies makes it possible to analyse different aspects of the transformation of urban mobility. The emergence of such trends with high-order interactions among space, time and the mentioned individual attributes indeed brings us new opportunities to integrate more knowledge into urban planning and decision-making system in urban areas.

In this regard and as a literature review, different location-based data sources and proposed spatial analysis have been taken into account in the identification of urban mobility and trip patterns have been considered and discussed. Furthermore, the most frequent models and methods in the literature will be introduced and various spatial and non-spatial aspects have been taken into account

LITERATURE REVIEW

The first efforts to learn human mobility patterns were associated with classic transport sciences. Since the nineteenth century and as time-use or time-budget studies, various measures have been taken to identify different activities during the day (Szalai, 1966). Transportation forecasting was one of the first research fields that made use of mobility analysis, and mobility patterns have been studied since the late 1950s. The first analytical models implemented pre-calculated probability distributions of possible urban trip patterns mainly based on land use and socio-demographic characteristics (Douglass et al., 1957).

Starting in the 2000s, this approach was gradually enriched by activity-based models, e.g., computerized models that use agent-based simulations, where the agents are modelled and driven by specific human activity such as work, leisure, and shopping (Kitamura et al., 2000). Over recent years and with the fast development of information and communication technologies (ICT) and intelligent transportation system (ITS), large quantities of digital traces and geo-referenced social media data plus transit smart cards and time table data that register individual activity and trip behaviour at both spatial and temporal scales have become available (Batty et al., 2012). These datasets enable planners and researchers to model and analyse spatio-temporal interactions in urban mobility based on variety of proxies on human activities (Han et al., 2016; Sun et al., 2014).

Large-scale studies showed human trajectories have a high degree of temporal and spatial regularity, each individual being characterized by a time-independent characteristic travel distance and a significant probability to return to a few highly frequented locations (Gonzalez et al., 2008). The diversity of spatio-temporal regularity was found to be constrained, providing an encouraging foundation for studying and analysing mobility (Song et al., 2010).

Another emerging area of urban mobility studies relies on network theory and statistical tools. These studies that termed as computational science focus on analysing social interactions and temporal attributes of mobility patterns (Hamedmoghadam et al., 2019). In a series of papers, GIS-based accessibility modelling and network analysis have been used to trip generation assessment and patterns of trip occurrence in accessibility infrastructure (Castanho et al., 2020), human mobility patterns with the support of location-based services (Ebrahimpour et al., 2020: Habibi et al, 2020), similarity and dissimilarity of the dynamic mobility patterns on the basis on spatio-temporal characteristics (Yuan et al., 2012).

Location tracking and location-based service patterns are widely being used in a growing number of applications and different levels (Toch et al., 2019: Kahvand et al, 2015). To contribute to the transformation of urban mobility, studies have focus on geographical area subdivision-based mobility patterns with distinct characteristics. Different clustering algorithms and feature extraction methods have been used to detect spatial operation patterns in urban mobility (Kang et al., 2016). Mobility behaviour analysis, trip distribution, activity identification, understanding spatio-temporal interactions and social characteristics are the most common ways that represents reliable sources to analyze mobility patterns in urban areas (Ali et al., 2016; Sun et al., 2016).

Various data mining methods have been developed to uncover transit behaviour patterns on the basis of heterogeneous geospatial datasets, including public transport-oriented and passenger-oriented approaches for mobility analysis (El Mahrsi et al., 2017), spatial affinity propagation with spatial-behavioural features in trip segments (Kieu et al., 2018), trip chaining methods for pattern estimation, validation and diversification (Li et al., 2018), and choice modelling for activity identification and analysis (Wang et al., 2017).

Over the past few years, many studies have been conducted to explore urban trip patterns using various modelling and analytic approaches based on massive human mobility data, such as optimization-based routing equilibrium models for congestion alleviation (Çolak et al., 2016), clustering-based correlated analyses of mobility similarities and relationships, low-level mobility pattern discovery and multi-scale exploration of social fragmentation (Schneider et al., 2013). With the availability of massive human mobility data, machine learning techniques have been playing a more and more important role in gaining a deep understanding of human mobility behaviour (Toch et al., 2019), ranging from movement pattern mining (Chen et al., 2016), mobility prediction (Ouyang et al., 2018), and movement mode classification to lifestyle discovering and prediction (Chen et al., 2019).

DISCUSSION

Travel behaviour analysis toward transformative urban mobility

Starting from the premise that the mobility is a fundamental issue, discovering the transformation of urban mobility impact on different parts of the urban area is essential. Mobility paradigm shifting in cities happens in a wide range of other contexts that are host of problems and challenges including urban accessibility degradation, lack of social equity, land use conflicts, urban sprawl, and social exclusion (Bibri, 2019: Naghdi et al, 2016). Given these issues, the transformation of urban mobility appraisal guidance includes a spectrum of various impacts through qualitative and quantitative assessments and comparison analysis (Camagni et al., 2002; Nielsen et al., 2012: Sarvar et al., 2011).

In-depth knowledge of spatio-temporal distribution of urban mobility is a key aspect in characterizing the behaviour of transit users in urban areas for mobility transforming identification. This information can provide valuable insight into urban trips analysis such as when they begin and end within complete day. Spatial observations of urban trip distribution can indicate infrastructure efficiency, transport accessibility and modality, and traffic congestions in urban areas. Mode share trends based on daily time, weather condition, season, and other features allow transit planners to remark mobility transformation to promote their services (Sun et al., 2016).

Since urban mobility trends are based on the particular purposes, utilizing integrated attributes like the trip duration, type and regularity can lead to assigning activities to individual stakeholders for the activity-based model. Home, work or educational units can be considered along with socio-demographic attributes for activity-based micro-simulations (Gan et al., 2020).

The proposed discussion starts with observations concerning the relationship between the spatial and non-spatial conceptualization of travel behavior based on activity identification along with priorities, types and scheduling. In fact, travel behavior is a part of complex hierarchical structures that include activity trends, mobility flows, spatial interactions, and finally, activity identification to derive mobility patterns in urban areas.

In general, the total number of daily stops, particularly between relatively distinct units constructs urban trips. Therefore, travel behavior can be defined as the spatial way sequenced segments of the urban trip take place. There have been considerable efforts extended to understanding the spatio-temporal characteristics and complexity of travel behavior using a variety of abstraction level in modelling (Pritchard et al., 2014).

Visualized representation of mobility patterns

Temporal distribution of urban mobility

The high resolution temporal distribution of boarding times during a 24-hour period includes the number of trips per minute for any moment. The main advantage of this diagram is the explicit representation of urban trip peaks in a day. The diagram in figure 1 indicates that the sharp peaks in urban mobility occur in starting (8 am) and ending (7pm) hours of working time in Seol, South Korea (Ali et al., 2016).

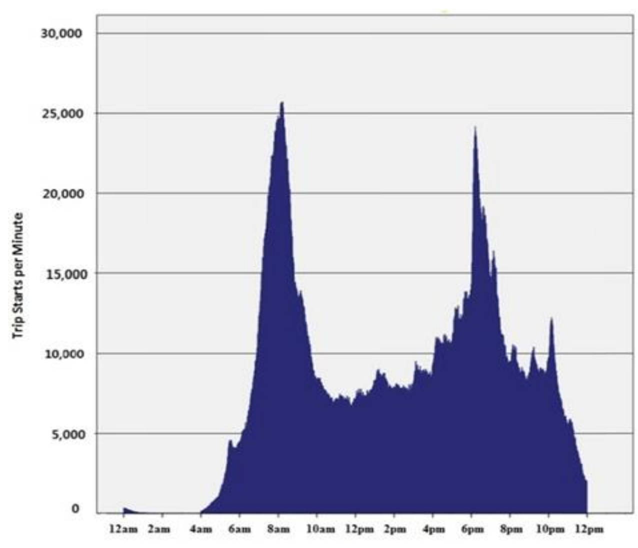

Figure 1. High temporal resolution of trip distribution (Ali et al., 2016).

Accurate distribution of mobility patterns based on temporal features along with public transport schedule, private vehicles flows, travel time tables, and qualifying transfer volume by different modes can lead to a large scale agent-based simulation model of urban mobility.

Advanced statistical approaches for travel behavior analysis and activity identification provide a new insight of mobility patterns to transit planning. Furthermore, it can be considered as an effective framework to monitor the transformation of urban mobility and transport infrastructure performance.

Spatial distribution of urban mobility

The trip patterns extracted from large-scale datasets at spatially-aggregated levels, as shown in figure 2, can efficiently contribute to travel behavior analysis in urban areas. These visualized representations of the spatial distribution of urban mobility cover a wide range of impacts, variables, flows, paradigm shifts, and attributes related to transportation network in urban areas (Bao et all., 2018). These GIS-based models can be used in mobility patterns recognition, travel behavior, activity identification, land use planning, and socio-economic impacts in urban areas. They also are the core of spatially integrated approaches for sustainability. The inclusion of urban trip patterns extracted from such spatial analysis significantly improve the performance of the transport system and logistic infrastructure. They can be an aggregated basis of different quantitative and qualitative comparison analysis for various purposes (Haselsteiner et al., 2015).

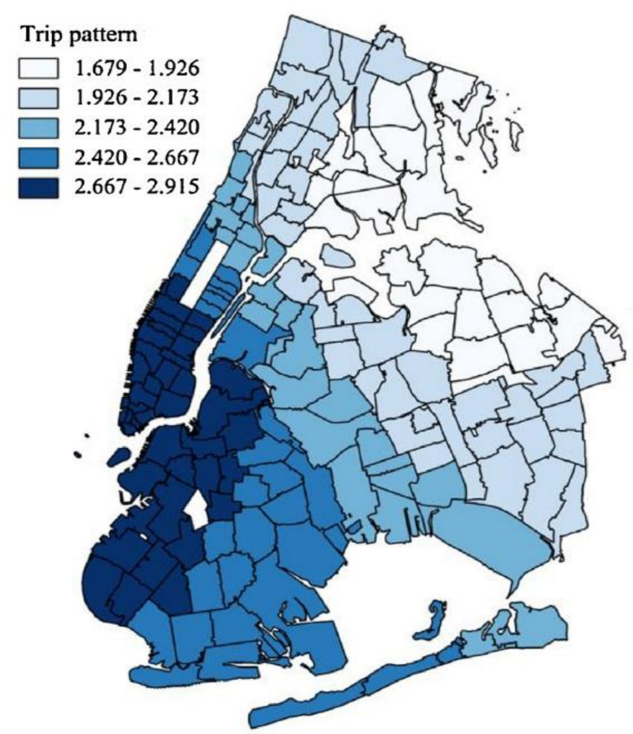

Figure 2. Spatial distribution of the coefficient of urban trip patterns variables (Bao et all., 2018).

- **Spatio-temporal flows of mobility**

As shown in figure 3, the total mobility flows entering a distinct region are inflow and the ones leaving a region for another denote outflow. Both flows track the mobility patterns between different regions of urban area. these flows are very applicable in risk assessment, transport management and particularly, the transformation of urban mobility studies. They can accurately reflect the spatio-temporal dependencies of urban mobility such as spatial correlation, traffic congestion and surrounding conditions.

Furthermore, it is possible to employ the spatio-temporal residual network analysis methods to model nearby and distant spatial dependencies of any two regions, temporal closeness, period and trends, dynamical aggregated outputs, and assigned weights. In this way, the effects of different components, internal structures and external factors on proposed flows can be evaluated (Zhang et al., 2017).

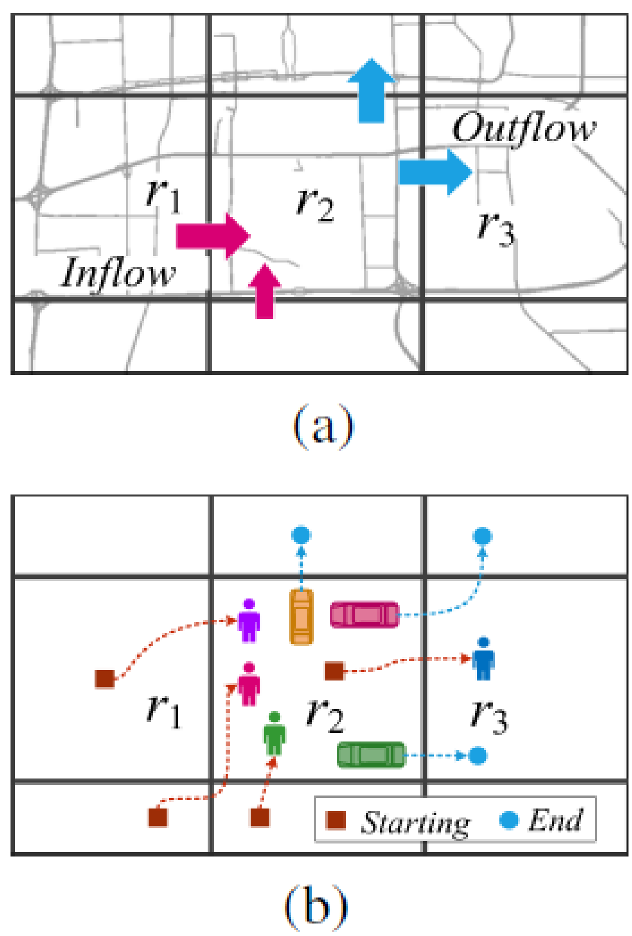

Figure 3. Regional mobility inflow and outflow (a) and measurements (b) - (Zhang et al., 2017).

Spatial interaction estimation

The emergence of different mobility monitoring systems brings new opportunities to integrate complex and higher-order interactions among space, time and attributes. Analytical frameworks and statistical techniques provide better understating and representation ways to better interpret mobility patterns and urban dynamics. In this regard, by using factorization model to decompose high-dimensional mobility data into specific patterns, from which we can extract key information by reasoning about the semantics of regions and activities in urban areas (Sun et al., 2016: Zaker Haghighi et al, 2014).

Once the urban trips are identified, additional attributes such as zone properties, coordinates, distances, and travel mode are considered to generate origin-destination matrixes (OD) for zone analysis. OD matrix integrates activity identification data to assign activities to individual users and trips for the activity-based model, as different spatial interactions, shown in figure 4. Spatial interaction models illustrate how different zones are functionally interdependent. They can also reflect the human-land relationship has long been a core topic in urban planning and transport studies, as well as the transformation of urban mobility.

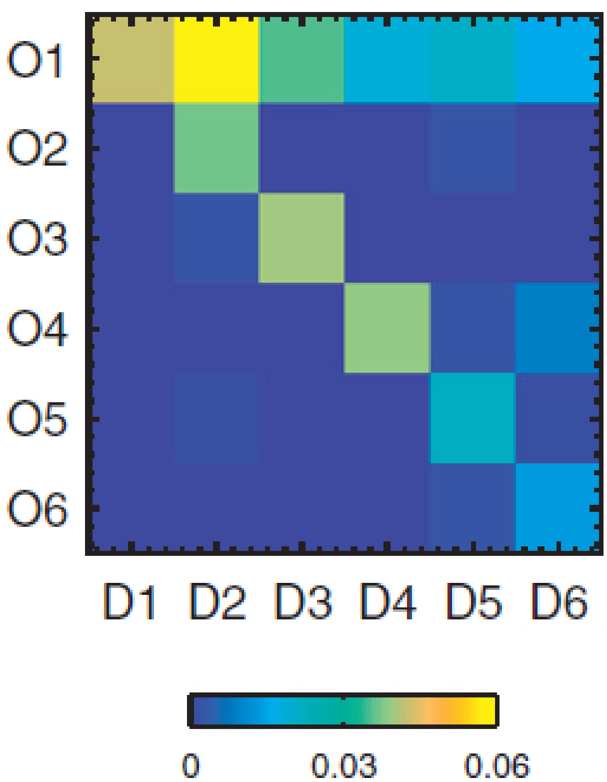

Figure 4. Spatial interactions based on distinct origin-destination for spatio-temporal patterns (Sun et al., 2016).

CONCLUSION

The present study investigated how the trip patterns and related spatial characteristics and variables can be extracted from different data sources to contribute to the transformation of urban mobility. Trip pattern information was estimated with the trip generation models developed based on electronic fare payment system data, transit smart card data, geo-referenced social media data, large scale global positioning system (GPS), trip flows based on the public transport system and scheduled time table, and road network attributes. Understanding the urban trip flows mobility patterns and their trends and paradigm shifts is an immense step toward sustainability in spatial planning. Geospatial Information System (GIS) plays an undeniable role in such field. With the advantages of spatio-temporal analysis, it is possible to evaluate the urban mobility dynamics based on trip behaviour, distribution of trips based on various conditions, activity identification, and departure time table of different public transport modes. As the transformation of urban mobility has direct effects on different aspect of society, understanding these changes can accelerate the creation and deployment of sustainable mobility and transport system in urban areas.

With the advances in computer science and technology, the Intelligent Transport Systems (ITS) are emerging as one of the best solution to tackle the transport system by providing accurate and real-time data. Advanced data mining techniques are implemented to derive the travel behavior patterns and characteristics to evaluate the unexpected trends in mobility dynamics.

The reviewed models extracted from proposed data sources by mean of GIS focus on providing a generalized data-driven framework to better utilize the increasing amount of individual-based mobility trends, underlying spatio-temporal structure of urban areas.

The questions regarding mobility patterns and required action as a response to trends, dynamics and complexity of urban areas are essential to spatial/transportation planning. Our review enriches the information in mobility data by discussing trip patterns in a multi-dimensional setting, accurate mapping and data analysis provided by GIS. Comprehensive understanding of spatio-temporal urban dynamics through collective transit mobility demonstrates great flexibility in studying several directions of transformative urban mobility such as trends in trip behavior, trip purposes, trip chain and transport modes. Proposed aspects of mobility in urban areas can be inferred and integrated to the GIS-based models and analysis to add a new dimension to the planning process. In this way, we can use spatial interaction, trip distribution and dependencies as priors to registering individual trip behavior analysis, offering new insights in mobility studies by enhancing transport system and infrastructure in urban areas.

DECLARATIONS

Author's contribution

Both authors contributed equally to this work.

Competing interests

The authors declare that they has no competing interests.

REFERENCES

Ali A, Kim J, Lee S. (2016). Travel behavior analysis using smart card data. KSCE Journal of Civil Engineering. May 1;20(4):1532-9. Google Scholar

Bao J, Liu P, Qin X, Zhou H. (2018). Understanding the effects of trip patterns on spatially aggregated crashes with large-scale taxi GPS data. Accident Analysis & Prevention. Nov 1;120:281-94. Google Scholar , https://doi.org/10.1016/j.aap.2018.08.014

Batty M, Axhausen KW, Giannotti F, Pozdnoukhov A, Bazzani A, Wachowicz M, Ouzounis G, Portugali Y. (2012). Smart cities of the future. The European Physical Journal Special Topics. Nov 1;214(1):481-518. Google Scholar

Bibri SE. (2019). On the sustainability of smart and smarter cities in the era of big data: an interdisciplinary and transdisciplinary literature review. Journal of Big Data. Dec 1;6(1):25.Google Scholar

Camagni R, Gibelli MC, Rigamonti P. (2002). Urban mobility and urban form: the social and environmental costs of different patterns of urban expansion. Ecological economics. Feb 1;40(2):199-216. Google Scholar, https://doi.org/10.1016/S0921-8009(01)00254-3

Castanho RA, Behradfar A, Vulevic A, Naranjo Gómez JM. (2020) Analyzing Transportation Sustainability in the Canary Islands Archipelago. Infrastructures. Jul;5(7):58. Google Scholar, https://doi.org/10.3390/infrastructures5070058

Chen R, Chen M, Li W, Wang J, Yao X. (2019). Mobility modes awareness from trajectories based on clustering and a convolutional neural network. ISPRS International Journal of Geo-Information. May;8(5):208. Google Scholar, https://doi.org/10.3390/ijgi8050208

Chen X, Shi D, Zhao B, Liu F. (2016). Mining individual mobility patterns based on location history. In2016 IEEE First International Conference on Data Science in Cyberspace (DSC) Jun 13 (pp. 252-259). IEEE. Google Scholar, **DOI:** 10.1109/DSC.2016.52

Çolak S, Lima A, González MC. (2016). Understanding congested travel in urban areas. Nature communications. Mar 15;7(1):1-8. Google Scholar

Costa PB, Neto GM, Bertolde AI. (2017). Urban mobility indexes: A brief review of the literature. Transportation research procedia. Jan 1;25:3645-55. https://doi.org/10.1016/j.trpro.2017.05.330, Google Scholar,

Douglass Carroll JD, Bovls HW. (1957). Predicting local travel in urban regions. Papers in Regional Science. 3(1):183-97.Google Scholar, https://doi.org/10.1111/j.1435-5597.1957.tb01599.x

Ebrahimpour Z, Wan W, Velázquez García JL, Cervantes O, Hou L. (2020). Analyzing Social-Geographic Human Mobility Patterns Using Large-Scale Social Media Data. ISPRS International Journal of Geo-Information. Feb;9(2):125. Google Scholar, https://doi.org/10.3390/ijgi9020125

Gan Z, Yang M, Feng T, Timmermans H. (2020). Understanding urban mobility patterns from a spatiotemporal perspective: daily ridership profiles of metro stations. Transportation. Feb;47(1):315-36. Google Scholar

Gheitarani N, El-Sayed S, Cloutier S, Budruk M, Gibbons L, Khanian M. (2020). Investigating the Mechanism of Place and Community Impact on Quality of Life of Rural-Urban Migrants. International Journal of Community Well-Being. Mar;3(1):21-38. Google Scholar

Gonzalez MC, Hidalgo CA, Barabasi AL. (2008). Understanding individual human mobility patterns. nature. Jun;453(7196):779-82. Google Scholar

Habibi K, Hoseini SM, Dehshti M, Khanian M, Mosavi A. (2020). The Impact of Natural Elements on Environmental Comfort in the Iranian-Islamic Historical City of Isfahan. International Journal of Environmental Research and Public Health. Jan;17(16):5776. Google Scholar, https://doi.org/10.3390/ijerph17165776

Hamedmoghadam H, Ramezani M, Saberi M. (2019). Revealing latent characteristics of mobility networks with coarse-graining. Scientific reports. May 17;9(1):1-0. Google Scholar

Han G, Sohn K. (2016). Activity imputation for trip-chains elicited from smart-card data using a continuous hidden Markov model. Transportation Research Part B: Methodological. Jan 1;83:121-35. Google Scholar, https://doi.org/10.1016/j.trb.2015.11.015

Haselsteiner E, Smetschka B, Remesch A, Gaube V. (2015). Time-use patterns and sustainable urban form: A case study to explore potential links. Sustainability. Jun;7(6):8022-50.Google Scholar, https://doi.org/10.3390/su7068022

Hegyi FB, Morgen H, Vendel M. (2019). Urban mobility in transformation: demands on education to close the predicted knowledge gap. Transforming Urban Mobility. Oct:114. Google Scholar

Kahvand M, Gheitarani N, Khanian MO, Ghadarjani RA. (2015). Urban solid waste landfill selection by SDSS. Case study: Hamadan. Environment Protection Engineering. 41(2).Google Scholar, doi 10.5277/epe150204

Kang C, Qin K. (2016). Understanding operation behaviors of taxicabs in cities by matrix factorization. Computers, Environment and Urban Systems. Nov 1;60:79-88. Google Scholar, https://doi.org/10.1016/j.compenvurbsys.2016.08.002

Khanian M, Marshall N, Zakerhaghighi K, Salimi M, Naghdi A. (2018). Transforming agriculture to climate change in Famenin County, West Iran through a focus on environmental, economic and social factors. Weather and climate extremes. Sep 1;21:52-64.Google Scholar, https://doi.org/10.1016/j.wace.2018.05.006

Kieu, L, M. Ou, Y, Cai, C. (2018). Large-scale transit market segmentation with spatial-behavioural features. Transportation Research Part C: Emerging Technologies, 90, 97-113. Google Scholar, https://doi.org/10.1016/j.trc.2018.03.003

Kitamura R, Chen C, Pendyala RM, Narayanan R. (2000). Micro-simulation of daily activity-travel patterns for travel demand forecasting. Transportation. Feb 1;27(1):25-51. Google Scholar

Li T, Sun D, Jing P, Yang K. (2018). Smart card data mining of public transport destination: A literature review. Information. Jan;9(1):18.Google Scholar, https://doi.org/10.3390/info9010018

Naghdi A, Khanian M, Rueentan M. (2016). The urban dilemmas in Iran marginal urban area; A case study of Kermanshah city. Journal of Civil Engineering and Urbanism.1:16-23. Google Scholar, PDF

Nielsen TA, Næss P. (2012). Activity based indicators of connections and access needs (ABICA). InAccessibility Instruments for Planning Practice: COST Action TU1002 (pp. 71-76). COST Office. Google Scholar

Ouyang X, Zhang C, Zhou P, Jiang H, Gong S. (2016). Deepspace: An online deep learning framework for mobile big data to understand human mobility patterns. arXiv preprint arXiv:1610.07009. Oct 22. Google Scholar

Pritchard JP, Moura F, e Silva JD, Martinez LM. (2014). Spatial analysis of transportation-related social exclusion in the Lisbon metropolitan area. Procedia-Social and Behavioral Sciences. Feb 5;111:440-9. Google Scholar, https://doi.org/10.1016/j.sbspro.2014.01.077

Sarvar H, Amini J, Laleh-Poor M. (2011). Assessment of risk caused by earthquake in region 1 of Tehran using the combination of RADIUS, TOPSIS and AHP models. Journal of Civil Engineering and Urbanism.;1(1):39-48. Google Scholar, PDF

Schneider CM, Rudloff C, Bauer D, González MC. (2013). Daily travel behavior: lessons from a week-long survey for the extraction of human mobility motifs related information. InProceedings of the 2nd ACM SIGKDD international workshop on urban computing Aug 11 (pp. 1-7). Google Scholar, https://doi.org/10.1145/2505821.2505829

Song C, Qu Z, Blumm N, Barabási AL. (2010). Limits of predictability in human mobility. Science. Feb 19;327(5968):1018-21. Google Scholar, DOI: 10.1126/science.1177170

Sun L, Axhausen KW. (2016). Understanding urban mobility patterns with a probabilistic tensor factorization framework. Transportation Research Part B: Methodological. Sep 1;91:511-24. Google Scholar, https://doi.org/10.1016/j.trb.2016.06.011

Sun L, Jin JG, Axhausen KW, Lee DH, Cebrian M. (2014). Quantifying long-term evolution of intra-urban spatial interactions. Journal of The Royal Society Interface. 2015 Jan 6;12(102): 1089. Google Scholar, https://doi.org/10.1098/rsif.2014.1089

Szalai A. (1966). The multinational comparative time budget research project: a venture in international research cooperation.Google Scholar, https://doi.org/10.1177/000276426601000401

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. Knowledge and Information Systems. Mar 5;58(3):501-23. Google Scholar

Wang Y, de Almeida Correia GH, de Romph E, Timmermans HJ. (2017). Using metro smart card data to model location choice of after-work activities: An application to Shanghai. Journal of Transport Geography. Jul 1;63:40-7. Google Scholar, https://doi.org/10.1016/j.jtrangeo.2017.06.010

Yuan Y, Raubal M. (2012). Extracting dynamic urban mobility patterns from mobile phone data. InInternational conference on geographic information scienceSep 18 (pp. 354-367). Springer, Berlin, Heidelberg.Google Scholar

Zaker Haghighi K, Gheitarani N, Khanian M, Taghadosi R. (2014). Examination of effects of urban street configuration on the amount of commercial buildings establishment (according to natural movement theory), Case study: Hamedan. European Online Journal of Natural and Social Sciences. Jan 23;3(1):pp-20.. Google Scholar

Zhang J, Zheng Y, Qi D. (2016). Deep spatio-temporal residual networks for citywide crowd flows prediction. arXiv preprint arXiv:1610.00081. Oct 1.Google Scholar