Relationships between mobile phone usage and activity-travel behavior
A review of the literature and an example

Wang, Yihong; Correia, Gonçalo Homem de Almeida; van Arem, Bart

DOI
10.1016/bs.atpp.2019.08.001

Publication date
2019

Document Version
Final published version

Published in
Advances in Transport Policy and Planning

CHAPTER FOUR

Relationships between mobile phone usage and activity-travel behavior: A review of the literature and an example

Yihong Wang[a,*], Gonçalo Homem de Almeida Correia[a,b], Bart van Arem[a]

[a]Department of Transport and Planning, Delft University of Technology, Delft, The Netherlands
[b]Department of Civil Engineering, University of Coimbra, Coimbra, Portugal
*Corresponding author: e-mail address: y.wang-14@tudelft.nl

Contents

Advances in Transport Policy and Planning, Volume 3
ISSN 2543-0009
https://doi.org/10.1016/bs.atpp.2019.08.001

Abstract

Almost everyone has a mobile phone today. In addition to calls and text messages, people are utilizing mobile apps and websites to connect to the world and explore different content anytime and anywhere. The use of smart phones generates billions of records, including spatiotemporal trajectories, and various mobile phone usage details, such as call duration, and frequency of visiting a certain type of website. Most transportation researchers have only focused on spatiotemporal traces, which represent activity-travel behavior of users. However, it is worth making full use of smart phone data to study how mobile phone usage is related to activity-travel behavior. This chapter first reviews the existing literature on the relevant topics to demonstrate the lack of research on the relationship between mobile internet usage and activity-travel behavior. Based on an 11-day dataset from Shanghai that includes not only spatiotemporal traces but also the frequencies of browsing different categories of mobile internet content (e.g., tourism and finance), we examine several relationships between mobile internet usage and activity-travel behavior.

Keywords: Mobile phone usage, Mobile internet usage, Mobile phone data, Spatio-temporal traces, Travel behavior, Activity patterns, Location choice, Variety seeking, Commuting behavior

1. Introduction

With the rapid development of Information and Communication Technologies (ICT), people have started using mobile devices in their daily lives. Most mobile devices do not only provide services to users, but also record information about the use of the device and sometimes also spatio-temporal traces (Li et al., 2011; Zhang and Sawchuk, 2012). Relative to other mobile devices such as wearable devices, mobile phones are most commonly used. People have traditionally used mobile phones to communicate with friends and families by making calls and using SMS (short message service). More recently, smart phones in addition allow visiting websites, subscribing to news, and playing online games, thanks to fast-growing mobile internet technologies. Consequently, every day, billions of data records are generated by mobile phones. Such mobile phone data often include spatiotemporal traces of users, which represent their actual movements (Ahas et al., 2010; Calabrese et al., 2014; Ratti et al., 2006). Many studies have explored how to measure activity-travel behavior from mobile phone traces, in terms of activity patterns (Diao et al., 2016; Järv et al., 2014; Yin et al., 2017), trip generation (Bwambale et al., 2017; Çolak et al., 2015), location choice (Chen et al., 2014; Molloy et al., 2017;

Y. Wang et al., 2017), mode choice (Phithakkitnukoon et al., 2017; Wang et al., 2010), departure time choice (Alexander et al., 2015), route choice (Bierlaire et al., 2013; Chen, 2013). Moreover, mobile phone data also include information about how users communicate with other people, such as call duration (Z.-Q. Jiang et al., 2013b; Wang et al., 2018a), as well as how they connect to internet services, such as frequency of visiting a website (Wang et al., 2018b; Z. Wang et al., 2017), both of which are generally called as mobile phone usage in this chapter.

Apparently, the two types of information in mobile phone data motivate two seemingly separate research directions: studying activity-travel patterns and studying mobile phone usage patterns. However, it is also worth combining these two types of information together and studying the relationships between mobile phone usage and activity-travel behavior (Ben-Elia et al., 2018; Ben-Elia and Zhen, 2018; van den Berg et al., 2013). The earliest research on travel and telecommunication originates from the 1980s when ICT were emerging and people were wondering if ICT, especially telecommuting, would reshape travel behavior (Mokhtarian, 1990; Salomon, 1986). Since then, it has been extensively debated whether telecommunication usage substitutes for travel (Salomon, 1998) or complements it (Mokhtarian, 2003). Nevertheless, the context of this debate is mostly outdated, and few studies have examined this relationship by considering mobile internet usage as a dominant usage of telecommunication today.

Based on the identified relationships (no matter if it is substitution or complementary), researchers attempted to characterize travelers by their mobile phone usage and further explain or predict their travel behavior (Bwambale et al., 2017; Wang et al., 2018a; Wang et al., 2018b) and even provide visiting location recommendations (Husain and Dih, 2012; Lian et al., 2015). This is regarded as a solution to travel behavior modeling using mobile phone traces, where personal attributes (e.g., socio-demographics) are absent due to privacy concerns, since increasingly more urban decision makers intend to prevent expensive traditional travel survey data. Researchers have also done the other way around: providing location-based services such as recommending internet content based on the places that a user has visited (Ahas and Mark, 2005; Lee et al., 2005).

In this study, we first present a review of the existing literature related to (1) mobile phone technology, (2) mobile phone usage, (3) activity-travel behavior that can be derived from mobile phone traces, and most importantly, (4) the relationships between mobile phone usage and activity-travel behavior. Since it is found that such relationships have not been studied adequately in the context of mobile internet usage, we continue our work with a case study in the city of Shanghai, China, to add recent empirical evidence to this research area. Using Shanghai Unicom WO+ Open Data Application Contest,[a] this is one of the first studies that use mobile internet usage data and mobile phone traces to address the following questions: (1) it addresses the question about the relationship between activity-travel and mobile phone usage in the mobile internet era by providing empirical evidence; and (2) it presents a possibility of accounting for the heterogeneity of activity-travel behavior revealed in mobile phone traces by using mobile internet usage data. At the end of this chapter, conclusions are drawn and future research directions are pointed out.

2. Literature review

This section consists of four parts. Part 1 and 2, respectively, present a review of the literature on mobile phone technology and the literature on mobile phone usage. The third part reviews the approaches that derive activity-travel behavior from mobile phone traces. Finally, the fourth part provides the results of a literature review on the relationships between mobile phone usage and activity-travel behavior, and based on this review develops a conceptual framework to understand this relationship.

2.1 Mobile phone technology

Mobile phones have played an important role in people's lives. They have not only been used as a communication device but also served as a sensing device to collect information from its users (Lane et al., 2010). This study mainly focuses on two types of user information: (1) mobile phone usage, and (2) spatiotemporal traces. In this subsection, we discuss the mobile phone technologies that enable the generation of spatiotemporal traces of users. There are mainly four location systems that can record mobile phone users' spatiotemporal traces: (1) cellular-network-based positioning system (Demissie et al., 2013), (2) GPS positioning system (Wolf et al., 2004), (3) Wi-Fi positioning system (Danalet et al., 2016), and (4) Bluetooth positioning system (Delafontaine et al., 2012). In this chapter, we limit our scope to cellular-network-based positioning system, which generates the most widely applied type of mobile phone data in travel behavior research (Wang et al., 2017).

[a] https://www.kesci.com/woplus/ (retrieved date: 5th January 2017).

Mobile phones are able to communicate with each other and connect to the mobile internet, based on cellular networks composed of transceivers that cover their respective land areas. With the movement of a mobile phone, it searches and connects to the nearest transceiver. This process is known as mobile phone positioning (Chen et al., 2016). Positioning data about such connections between users and transceivers are recorded mostly for cellular network operators' own purposes (e.g., billing), which are often not related to transportation, whilst as a by-product, they have been utilized by urban decision makers and researchers to estimate and understand mobility patterns (Wang and Chen, 2018). Because such data are in terms of spatiotemporal traces, researchers named them as mobile phone traces (Jiang et al., 2013a).

Mobile phone traces can be categorized into event-driven traces and network-driven traces (Pinelli et al., 2015). Call detail records and records of internet connections belong to the former one since the production of these data is triggered by user events, including usage of calls, SMS, and internet (Pinelli et al., 2015). Network-driven data are generated regardless whether people are using phones, but either in a periodic way or when a phone moves between two areas. Due to the nature of event-driven traces, their sampling is usually infrequent and could be biased to specific locations, e.g., home locations, and times, e.g., during the evenings; on the other hand, the sampling rate of network-driven traces is relatively higher and stable over time (Calabrese et al., 2014).

Spatial inaccuracy has always been an issue if mobile phone traces are used to estimate locations and represent individual mobility (Ahas et al., 2007). There are mainly two causes: (1) the difference between the actual location of a user and the location of the transceiver that the user is connecting to, and (2) the possibility of a user switching the connection between towers due to signal jumps even if the user is not moving (Alexander et al., 2015; Wang and Chen, 2018). To solve the first problem, the simplest way is to regard the transceiver's location or its Voronoi cell as a proxy for the user's location (Montjoye and Smoreda, 2014). Some telecom providers can estimate locations with a higher accuracy based on triangulation with several factors including the number of surrounding cells and received signal strength. The accuracy can reach about 100–500 m in urban areas and 400–10,000 m in rural areas, reported in a Chinese study (Wang et al., 2017b). Qi et al. (2016) named the second problem as the oscillation problem, to which Wang and Chen (2018) have presented an in-depth review on the solutions, including heuristic rules, spatiotemporal clustering, etc. Those algorithms can be used to preprocess mobile phone traces before conducting activity-travel behavior analysis.

2.2 Mobile phone usage

While in the past mobile phone usage referred to making calls and sending SMS text, nowadays it also includes using mobile internet services such as browsing the internet. All these kinds of mobile phone usage can be measured to quantify user preferences, such as the preference for longer calls or the preference for a certain type of content on the internet. Researchers have observed that different people use mobile phones in different ways (Sey, 2011), and they have further investigated whether personal characteristics, such as socio-demographic attributes (Blumenstock et al., 2010) and socio-economic attributes (Rahmati et al., 2012), would influence how people use mobile phones.

In the early stage of mobile technology when mobile penetration rate was not as high as it is today, researchers noticed that mobile phone usage and access actually differed by socio-economic profile, better known as the "mobile divide" or "digital divide" (Blumenstock and Eagle, 2010; Compaine and Kimmelman, 2001; Rice and Katz, 2003). For example, only wealthy people could afford mobile phones or mobile services during that period. Nevertheless, we have now entered an age where mobile phones have penetrated almost everywhere (Asongu, 2015; Thulin and Vilhelmson, 2007). While people across different societal segments all own mobile phones, the ways in which they use mobile phones still vary considerably.

Using the interview data of 1481 children and 1505 adolescents, Thomas et al. (2009) found that people in Germany with a lower socio-economic status used mobile phones relatively longer per day. In the empirical study by Blumenstock et al. (2010) using call detail records with complementary survey data from Rwanda, men were found to make more outgoing calls and receive less incoming calls than women. Moreover, the users owning televisions and the ones owning refrigerators (both indicating a higher economic status in Rwanda at that time) had longer daily call duration, compared to the others.

However, such research results have gradually become irrelevant and even invalid because fewer people are making calls, and very few people are still sending SMS text in the mobile internet era (Ofcom, 2013). Instead, people are using apps for countless functions, including, but not limited to, browsing the internet, sending emails, playing online games and instant messaging. Researchers have shifted their focus to mobile internet usage and started figuring out that mobile internet usage also differs among people from different population segments. Rahmati et al. (2012) carefully selected three groups of 34 mobile users from Houston, the United States, with high, low and very low socio-economic status, respectively, mainly based on household income. In their sample, users with a lower socio-economic status accessed mobile internet services more frequently. In addition, people with different socio-economic status were found to prefer different categories of websites. Pearce and Rice (2013) conducted a survey in Armenia and collected the data from 1420 voluntary and anonymous adults. They found that not only socio-economic (i.e., income) but also socio-demographic (e.g., gender, age and education) differences significantly influence mobile internet access as well as mobile internet activities. In the Netherlands, a survey was conducted from 2010 to 2013 to create a panel that consists of over 108,000 people representative of the Dutch population, and their demographics and internet usage (including mobile internet usage) were collected (van Deursen et al., 2015). The results showed that different people used internet for different purposes. For example, men, younger people, higher educated people and people with higher than average incomes significantly had more internet activities especially for personal development. Overall, while personal attributes are always an important factor influencing mobile phone usage, the mobile phone usage patterns of people from different socioeconomic or sociodemographic strata vary between different countries, for different purposes, and could even change over time.

In addition to using socio-economic strata to explain the differences in mobile phone usage, researchers have done the other way around: using mobile phone usage to predict socio-economic information (Frias-Martinez et al., 2013; Soto et al., 2011). This kind of research is necessary as well because it is too expensive to carry out traditional census surveys nationwide, and at the same time, survey results are very likely to be soon outdated (Calabrese et al., 2013). Comparably, mobile phone data are cheaper to obtain and faster updated, thus being able to help the government monitor socio-economic dynamics in a certain area.

2.3 Deriving activity-travel behavior from mobile phone traces

2.3.1 Stay extraction

Algorithms have been designed to extract trips and derive origin-destination (OD) information from mobile phone traces (Chen et al., 2014). Among all the spatiotemporal traces, they distinguish where users stay from where users pass by, and all the detected stay points can further be used to calculate stay areas, finally regarded as trip origins and destinations (Alexander et al., 2015). In general, the extraction of a stay point depends on two scale parameters, a time threshold and a distance threshold. A stay point is regarded as a sequence of traced positions where the distance between any pair of positions is less than a distance threshold, and the time spent at these positions is greater than a time threshold. A stay area is defined as a set of stay points which are close in space but far away in time. In addition, such methods are able to solve the problems of false movements, caused by mobile signal jumps between the towers (Alexander et al., 2015). After these procedures, activity locations can be determined, but activity purposes still need to be inferred with the use of complementary information (Jiang et al., 2017).

2.3.2 Activity purpose detection

To detect activity purposes, researchers reference the ground-truth spatial information, such as the information of POIs (points of interest) around activity locations (Demissie et al., 2015; Phithakkitnukoon et al., 2010). A more advanced approach is to calibrate a machine learning model (e.g., a decision tree) using travel survey data or other ground-truth mobility data, which associates activity purposes with several explanatory variables (Liu et al., 2013). Such a model can further be applied to mobile phone traces to label trip destinations with activity purposes. Without the availability of complementary information, arbitrary parameters can be set to infer home and work locations of mobile users based on general knowledge (e.g., most people stay home at night), and activity purpose can then be labeled as either home, work or other activity (Ahas et al., 2010).

2.3.3 Estimating other mobility information

Time-of-day information (i.e., start and end times of a trip or an activity) can also be estimated, which can help estimate the daily activity schedule of a traveler (Alexander, 2015). The accuracy level of time-of-day information is largely dependent on the temporal sampling rate of mobile phone traces. Observing the daily schedules of an individual across several days can help understand the rhythms of activity-travel behavior and better determine meaningful locations for this person (e.g., home and work locations). It is also possible to estimate mode and route choices, only given the mobile phone traces of a high temporal sampling rate as well as a high spatial resolution (Chen, 2013; Wang et al., 2010).

2.3.4 From sample to population

Notwithstanding the high mobile penetration rate everywhere, most of the times, researchers can only get access to a sample of limited size. Sometimes it is because that mobile network companies who provide mobile phone data do not dominate the market (Calabrese et al., 2013). It is also very likely that they do not want to expose the data of all of their users for commercial and privacy reasons (e.g., Laurila et al., 2012; Montjoye and Smoreda, 2014). Due to the sampling process, problems may arise if researchers aim to estimate not only individual travel behavior but also travel demand of a given population (Wesolowski et al., 2013). The sampled users might not be distributed geographically in the way as the population is (Kang et al., 2012). To solve this issue, Calabrese et al. (2011) compared the spatial distribution of the users' detected home locations and the one of the population revealed in the census data, and they calculated an expansion factor for each zone to upscale users to population. Another approach is to validate the movements derived from mobile phone traces by using the traffic ground truth data. Iqbal et al. (2014) scaled up the estimated OD matrix by using the scaling factors which would lead to better matches with the observed traffic counts.

2.4 Relationships between mobile phone usage and activity-travel behavior

The relationship between telecommunication and travel is a long-time debatable topic. This issue has been extensively discussed because researchers have observed two opposing possible effects of ICT on travel: either a substitute relationship or a complementary relationship. (Kamargianni and Polydoropoulou, 2013; Nobis and Lenz, 2009; Salomon, 1986). In recent years, researchers have especially focused on the relationship between mobile phone usage and travel, and they found that the actual relationships are more complex (Aguiléra et al., 2012; Mokhtarian, 2009), as there are many linkages between different dimensions of activity participation, travel patterns and mobile phone usage (Ben-Elia et al., 2014; Srinivasan and Raghavender, 2006).

In Section 2.2, we have already explained how mobile phone usage is dependent on personal attributes including socio-economic and socio-demographic ones. In fact, in most travel behavior models, such personal attributes are also assumed to be one of the major factors influencing behavioral heterogeneity among a given population (Rasouli and Timmermans, 2014). Extensive research has found that travel preferences are significantly different between older and younger people (Bernhoft and Carstensen, 2008;

Moschis and Ünal, 2008), between people with higher and lower household income (Lu and Pas, 1999), between people owning cars and not owning cars (van Wee et al., 2002), etc. In summary, both mobile phone usage and activity-travel behavior are influenced by personal attributes.

Based on this conceptual framework, it is not difficult to deduce that mobile phone usage and activity-travel behavior are somehow related to each other. For example, younger people tend to make more trips and use mobile phones more frequently (Yuan et al., 2012). This kind of deduction is quite useful not only for understanding the relationship between mobile phone usage and travel, but also for modeling heterogeneity in travel behavior using mobile phone data since traditional personal attributes are missing there in most cases for privacy reasons (Blondel et al., 2015).

It is also reasonable to add direct interactions between activity-travel behavior and mobile phone usage in our conceptual framework. For example, it can be hypothesized that those who travel more would also make more use of mobile phones while on the move. Also, driving calls are quite frequent but less on public transit, where internet usage is more pervasive. Despite the microscopic mechanisms of such interactions, the main idea of our conceptual framework still holds: mobile phone usage can be used to model heterogeneity in travel behavior.

Yuan et al. (2012) found the correlation between mobile phone usage, in terms of call frequency, and travel behavior, in terms of activity space, across different age groups. Bwambale et al. (2017) suggested utilizing call behavior, such as call frequency and duration, to explain the heterogeneity in trip generation behavior, since this information, supplementary to mobile phone traces, is less privacy-sensitive but still related to some characteristics of a person. However, mobile phones are less used for calls today (Ofcom, 2013), making call behavior a less useful indicator; in contrast, people spend more time on mobile internet services. Moreover, mobile internet usage may reflect more detailed information about one's specific interests and lifestyles. Therefore, mobile internet usage data, if available, should encompass a better reflection of individuals' traits (Wang et al., 2018b), whilst not much research has been done in this regard possibly due to the lack of such data. The following part of this chapter attempts to fill this gap by carrying out a case study on the relationships between mobile internet usage and activity-travel behavior.

3. Case study

The case study is conducted in Shanghai, China, one of the most populated and fastest growing cities all over the world. We are allowed to access a sample dataset of Unicom mobile users. As one of the three mobile carriers in China, Unicom was reported to have had about 270 million users, more than 20% of the population in China, by the beginning of 2017. In the provided dataset, each anonymous user ID corresponds to not only their mobile internet usage but also their spatiotemporal traces from 27th of December 2015, to 6th of January 2016. The study period includes a new year's holiday from 1st of January to 3rd January.

In the data collection process, every trace of a user would be recorded once the user had any mobile phone activity, in terms of a call, SMS text, a voice mail, or an internet connection. However, for privacy reasons, the data provider aggregated the traces hour by hour for each user. Thus, the provided dataset only includes the location where a user stayed for the longest time within an hour. If a user did not have any mobile phone activity within that hour, we are not able to know where the user was, and it is called a missing trace.

To prevent the impact of missing traces on our further analysis, we only target the 46,007 users who had spatial records for at least 80% of the total hours during the study period. According to the data provider, due to the inherent detection inaccuracy, the actual position of a trace is estimated to lie within the 200×200 m square of which the center is the detected point. This spatial error is reasonably small and acceptable for our further analysis.

The mobile internet usage data were also aggregated by the data provider, who classified a select number of apps and websites into different categories. As a result, there are 13 categories of mobile internet content in total, including "finance," "food," "news," "housing," "car," "entertainment," "education," "job," health," "game," "shopping," "tourism," and "sports." Finally, the page view counts of each user are provided, respectively, for the 13 categories. According to the data provider, different apps may have different ways to count such "page views." For example, in some cases, they count the times an app has been opened; in some other cases, they count the times an app has been interacted with users. Therefore, such page views should only be compared across categories after being normalized.

4. Methodology

Fig. 1 presents the flowchart of the research methods for the case study. First, the indicators of mobile internet usage, namely preferred category of mobile internet content and total usage intensity, can be calculated

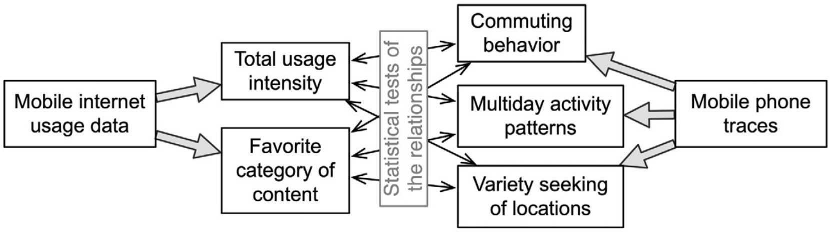

Fig. 1 The flowchart of the research methods for the case study.

for each user using mobile internet usage data. Second, the indicators of activity-travel behavior, including commuting behavior, variety seeking of locations, and multiday activity patterns, can also be calculated for each user using mobile phone traces. Finally, the relationships can be statistically tested between the indicators of mobile internet usage and the indicators of activity-travel behavior.

4.1 Indicators of mobile internet usage

This study considers an individual's mobile internet usage, in terms of the frequencies of browsing different categories of websites and apps via mobile internet over several days. More specifically, this information is provided in two indicators: (1) the frequency of browsing all contents, which reflects an individual's general mobile internet usage intensity, and (2) one's favorite category of mobile internet content, which reflects an individual's lifestyle and interest.

Let f_{un} indicate the frequency of browsing a category of mobile internet content n (e.g., finance or shopping) through mobile apps and/or websites by an individual u across several days. Given this, the two indicators of one's mobile internet usage during a period can be derived: (1) one's favorite category of mobile internet content N_u, and (2) the frequency of browsing all mobile internet contents F_u, which is further classified into two levels: high usage (higher than the median), and low usage (lower than the median), designated by a dummy variable F_u'.

4.2 Stay extraction from mobile phone traces

Stay points need to be distinguished from pass-by points among all mobile phone traces, and signal jumps should be reduced. An extensive literature has discussed these problems as well as their case-by-case solutions. In this study, we adopt the approach and parameter settings suggested by Alexander et al. (2015). Consider T_{ui} as the i-th spatiotemporal trace of an individual u, including three elements lon_{ui}, lat_{ui}, and $time_{ui}$ which represent longitude, latitude and timestamp, respectively.

First, for each user, the traces that are spatially close (within 300 m) to their subsequent observations need to be distinguished and sets of geographically close traces are obtained. Second, the medoid of the coordinates within each set is calculated. Third, the hierarchical clustering algorithm is applied to consolidate the sets that are close in space but far apart in time, using 500 m as the threshold. As a result, if the distance between two sets is shorter than 500 m, they are combined as a cluster. Fourth, the medoid of the coordinates within each cluster is calculated. Fifth, a duration threshold is assumed to identify whether a user stayed or passed by, and finally we can know where a user stayed for an activity and whether it is a location where the user had visited before. In our case study, it is stipulated that at least two consecutive traces close in space can determine a stay point, which will necessarily lead to overlooking some short activities; however, this is the best that can be done to extract stay points with these data.

4.3 Indicators of activity-travel behavior

In this study, we specifically focus on three aspects of activity-travel behavior: (1) commuting behavior, (2) variety seeking of locations, and (3) multiday activity patterns.

4.3.1 Commuting behavior

Home and work locations (if any) should be detected for each user at first. We apply the thresholds and rules mainly following the approach of Alexander et al. (2015). For each user, home location is defined as the location with the most stay traces from 7 to 8 a.m. on weekdays, on weekends, and on holidays. Work location is then defined to be the place to which one cumulatively traveled the maximum distance from home, max(vd), where v is the number of visits between 8 a.m. and 7 p.m. on weekdays, and d is the distance of a place from home. In addition, if a user visits the detected work location fewer than 2 days per week, it is not regarded as a work location. We further label the stay traces at the detected home location as home activity. The same applies to labeling work activity, and the remaining stay traces are labeled as secondary activity. The drawback of this approach is that only stable home and work locations can be detected.

After the process described above, we can generate two indicators of one's commuting behavior: (1) a dummy variable C_u stating whether user

u is a commuter, and (2) the commuting distance CD_u of user u if $C_u = 1$, further classified into two levels: longer commuting distance (longer than the median) and shorter commuting distance (shorter than the median), designated by CD_u'.

4.3.2 Variety seeking of locations

Another aspect of behavior to investigate is variety seeking of locations. People have been shown to have significantly different preferences in variety seeking of locations (Leszczyc et al., 2000; Leszczyc and Timmermans, 1997). Some people tend to explore new locations as much as possible, whilst the others tend to visit the places that they are familiar with (Pappalardo et al., 2015). We indicate one's variety seeking of locations by calculating the number of distinct locations L_u that user u has visited during the study period, and L_u is further classified into two levels: high variety seeking of locations (higher than the median) and low variety seeking (lower than the median) of locations, designated by L_u'.

4.3.3 Multiday activity patterns

Activity patterns are related to one's choices of activity type, frequency, sequence, start time and duration (Arentze and Timmermans, 2004). In our study, we especially focus on activity type and duration. For each individual, we calculate the share of time used for out-of-home activity within each day, represented by AP_{ud}, which means the proportion of out-of-home activities of user u on day d. Using the longitudinal mobile phone traces, we can observe multiday activity patterns of each user, which can further be clustered using the k-means clustering algorithm. The number of clusters can be determined by using the DB-index, which can indicate the compactness of a clustering solution (Davies and Bouldin, 1979). CL_u is used to designate which cluster user u belongs to.

4.4 Relating mobile internet usage to activity-travel behavior

We have two categorical indicators of mobile internet usage, N_u and F_u', and we have four categorical indicators of activity-travel behavior, C_u, CD_u', L_u' and CL_u. Pearson's chi-squared test is used to examine the statistical dependence between these variables (McHugh, 2013).

5. Results and discussion

5.1 Activity-travel behavior

Based on the detection algorithms, around 30% of mobile users are identified as commuters, and the distribution of their commuting distances is shown in Fig. 2. While the shape of the distribution looks similar to the ones found in Boston, Milan, etc. (Kung et al., 2014), the median and the mean of commuting distance are significantly higher in Shanghai, which are about 7.7 and 10 km, respectively. This is reasonable because of the large scale of the city, and also the figures are very close to the ones reported by the urban authority (Lu and Gu, 2011).

Fig. 3 shows the distribution of unique number of visited locations across the users during the 11 days. The median and the mean of the distribution are 3 and 3.125, respectively, indicating that people only visited three different places on average. It should be noted again that the detection algorithms used in this study tend to overlook short activities, as a side effect of stay extraction; therefore, it is likely that we have underestimated the unique numbers of visited locations. However, the impact of this underestimation is not huge because we do not focus on abstract values and we only group people into those with high variety seeking of locations and those with low variety seeking of locations.

The proportion of out-of-home hours is calculated for each user on each day, and each user can further be described by a vector of such proportions across 11 days. Based on these vectors, the users are clustered by applying the

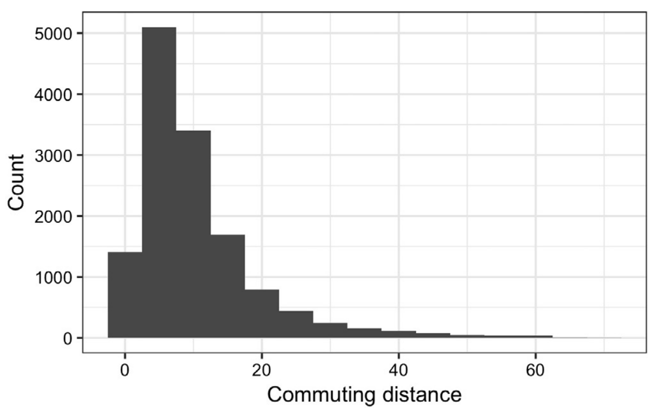

Fig. 2 The histogram of commuting distance (km).

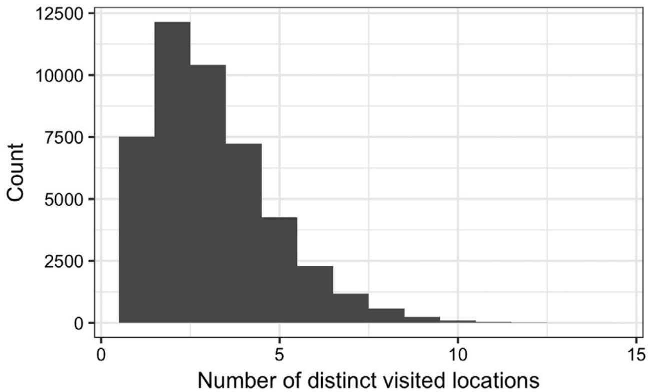

Fig. 3 The histogram of unique number of visited locations.

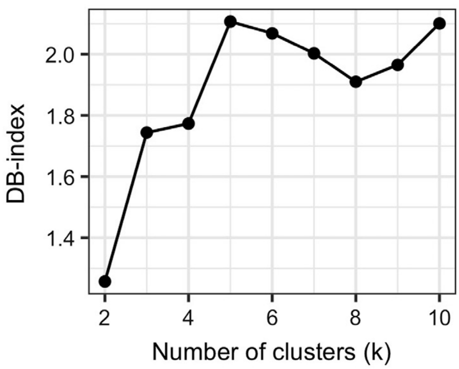

Fig. 4 The DB-index of clustering multiday activity patterns.

k-means algorithm. We consider the range of k from 2 to 10, and DB-index is calculated in each case to indicate the compactness of clusters, as shown in Fig. 4. A lower DB-index indicates more compact clusters.

While it can be observed that the clusters are most compact when $k=2$, we also investigate the clusters when $k=3$ and $k=4$, as shown in Fig. 5, for the sake of interpretation. Note that day 1 is Sunday; day 6, 7 and 8 are new year's holiday; the other days are weekdays. It is not difficult to figure out that cluster 1 in the first case ($k=2$) can somehow be decomposed into cluster 1 and cluster 2 in the second case ($k=3$). Cluster 2 in the second case ($k=3$) seems to represent the pattern of a typical commuter with 30% of time being not at home on weekdays on average. Cluster 1 in the second case ($k=3$) is relatively difficult to interpret, but it seems to further be decomposed into cluster 3 and 4 in the third case ($k=4$), which,

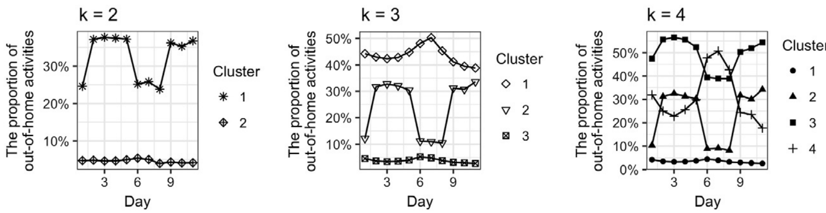

Fig. 5 The clusters of multiday activity patterns.

respectively, represent the commuters who stayed less time at home and the people who were more active on weekend and holiday. Considering both cluster compactness and interpretability, we use four clusters to distinguish multiday activity patterns, and cluster 1, 2, 3, and 4 are named as "inactive traveler," "typical commuter," "active commuter," and "weekend traveler," respectively.

5.2 The relationships between activity-travel behavior and mobile internet usage intensity

According to the results of our statistical tests, people with different intensity levels of total mobile internet usage seem to have significantly different activity-travel behavior, as shown in Fig. 6. First, people using more often mobile internet are more likely to be a commuter and have longer commutes. Second, people with higher usage intensity level also visited more distinct locations than the others during the 11 days. Third, those who frequently used mobile internet spent more time away from home in general. Especially, a clear difference in total usage intensity can be observed between inactive users and typical commuters. On the other hand, the difference between the other two clusters is not very significant.

A common pattern behind these observations is that people who travel more and longer tend to be active mobile internet users as well. A similar finding was reported by Yuan et al. (2012), who observed the positive correlation between high call frequency and larger activity space. We substantiate such a complementary relationship in the context of mobile internet.

5.3 The relationships between activity-travel behavior and favorite category of mobile internet content

Fig. 7 shows the statistical test results of the relationships between activity-travel behavior and favorite category of mobile internet content. In general, dependence can be found between each pair of variables as indicated by the

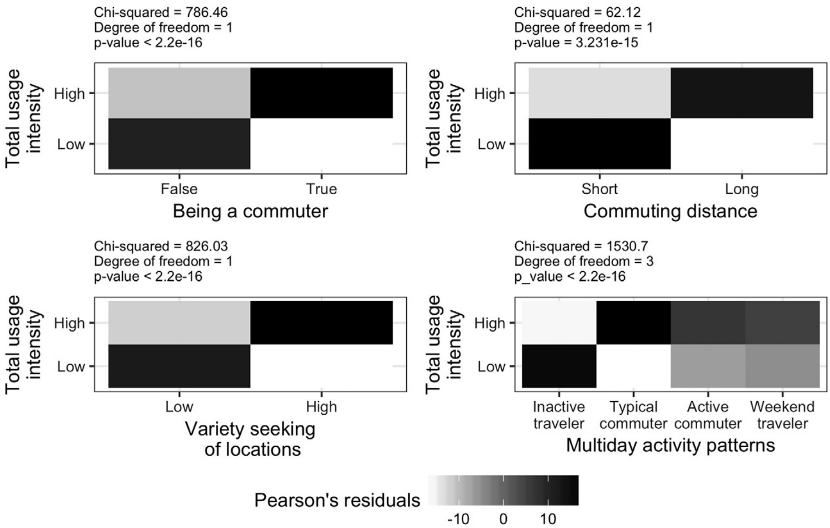

Fig. 6 Associations between activity-travel behavior and mobile internet usage intensity.

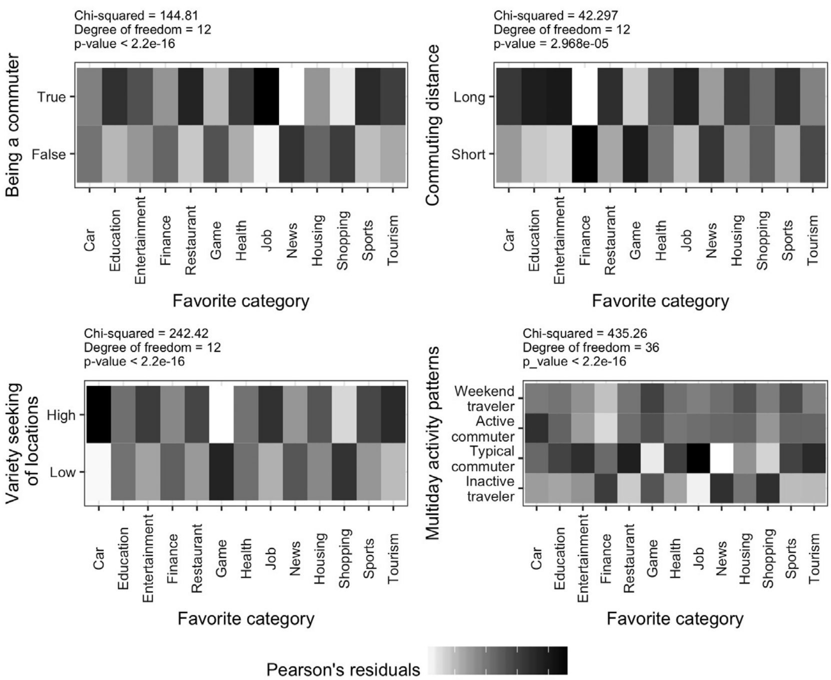

Fig. 7 Associations between activity-travel behavior and favorite category of mobile internet content.

low P-values. Especially, some associations between specific categories stand out. First, a commuter significantly preferred job-related content compared to a non-commuter. The other categories of content that interested commuters include restaurant and sports. On the other hand, a non-commuter was more likely to be attracted to the content related to online shopping and news. Second, a user with a shorter commute was significantly attracted to the content related to finance and game; in contrast, a user with a longer commute was more interested in the content related to education and entertainment. Third, those who visited more distinct locations seem to be the ones who were interested in the content related to car and tourism, whilst those who visited fewer distinct locations preferred the content related to game and online shopping. Fourth, it is hard to distinguish the preference of weekend travelers and active commuters, except that active commuters are significantly more interested in car-related content, compared to the others.

It is difficult to reason the significant associations merely based on such observations. However, some of them are quite consistent with common sense. For example, typical commuters were interested in job-related content; inactive travelers spent more time on games and online shopping; those who visited more distinct locations preferred the content related to car and tourism.

6. Conclusions and recommendations

This chapter has presented a literature review on the relationships between mobile phone usage and activity-travel behavior, and performed a case study, as a complementary example, to empirically investigate the relationships in the context of mobile internet. In Section 2, we built a simple conceptual framework to help understand the relationships between mobile phone usage and activity-travel behavior through literature review: they are related to each other because they are both dependent on personal attributes such as socio-economic and socio-demographic attributes. In Section 3–5, we used a mobile phone dataset from Shanghai, China, to inspect the relationships between activity-travel behavior of the users, revealed in spatiotemporal traces, and their mobile internet usage, including the frequencies of browsing different categories of content through mobile apps and websites. Some significant and interpretable relationships that we found are highlighted as follows:

- Those who traveled more and longer were likely to use mobile internet more often.
- Commuters were more interested in job-related content.
- Inactive travelers spent more time on games and online shopping.
- Those who visited more distinct locations preferred the content related to car and tourism.

Based on our study, a couple of research directions can be further investigated. First, more aspects of activity-travel behavior can be included in this kind of analysis. In our study, we only considered activity pattern and location choice mainly due to the relatively lower sampling rate of our data (i.e., one trace per hour); however, it is possible to detect travel mode choice, departure time choice and even route choice with higher-resolution data, and the relationships between mobile internet usage and these choices can then be examined. Second, although we only explored the statistical dependence between some indicators of mobile internet usage and activity-travel behavior, attempts could be made to build explanatory travel behavior models based on our findings, by using both mobile phone traces and mobile internet usage data. Such models can incorporate mobile internet usage as an element to distinguish different population segments and further explain behavioral heterogeneity.

Acknowledgments

We would like to express our gratitude to the Shanghai Unicom WO + Open Data Application Contest for making the mobile phone data available for this research. Thanks go also to the TRAIL research school and the Dutch Organization for Scientific Research (NWO) for sponsoring the first author for his PhD study. The assigned grant code is 022.005.030.

References

Aguiléra, A., Guillot, C., Rallet, A., 2012. Mobile ICTs and physical mobility: review and research agenda. Transp. Res. A Policy Pract. 46, 664–672. https://doi.org/10.1016/J.TRA.2012.01.005.

Ahas, R., Mark, Ü., 2005. Location based services—new challenges for planning and public administration? Futures 37, 547–561. https://doi.org/10.1016/J.FUTURES.2004.10.012.

Ahas, R., Laineste, J., Aasa, A., Mark, Ü., 2007. The Spatial Accuracy of Mobile Positioning: Some Experiences with Geographical Studies in Estonia, in: Location Based Services and TeleCartography. Springer, Berlin Heidelberg, Berlin, Heidelberg, pp. 445–460. https://doi.org/10.1007/978-3-540-36728-4_32.

Ahas, R., Silm, S., Järv, O., Saluveer, E., Tiru, M., 2010. Using Mobile positioning data to model locations meaningful to users of Mobile phones. J. Urban Technol. 17, 3–27. https://doi.org/10.1080/10630731003597306.

Alexander, L.P., 2015. Cell Phone Location Data for Travel Behavior.

Alexander, L., Jiang, S., Murga, M., González, M.C., 2015. Origin–destination trips by purpose and time of day inferred from mobile phone data. Transp. Res. C 58, 240–250. https://doi.org/10.1016/j.trc.2015.02.018.

Arentze, T.A., Timmermans, H.J., 2004. A learning-based transportation oriented simulation system. Transp. Res. B Methodol. 38, 613–633. https://doi.org/10.1016/j.trb.2002.10.001.

Asongu, S., 2015. The impact of mobile phone penetration on African inequality. Int. J. Soc. Econ. 42, 706–716. https://doi.org/10.1108/IJSE-11-2012-0228.

Ben-Elia, E., Zhen, F., 2018. ICT, activity space–time and mobility: new insights, new models, new methodologies. Transportation 45, 267–272. https://doi.org/10.1007/s11116-018-9870-y.

Ben-Elia, E., Alexander, B., Hubers, C., Ettema, D., 2014. Activity fragmentation, ICT and travel: An exploratory Path Analysis of spatiotemporal interrelationships. Transp. Res. A Policy Pract. 68, 56–74. https://doi.org/10.1016/J.TRA.2014.03.016.

Ben-Elia, E., Lyons, G., Mokhtarian, P.L., 2018. Epilogue: the new frontiers of behavioral research on the interrelationships between ICT, activities, time use and mobility. Transportation 45, 479–497. https://doi.org/10.1007/s11116-018-9871-x.

Bernhoft, I.M., Carstensen, G., 2008. Preferences and behaviour of pedestrians and cyclists by age and gender. Transport. Res. F: Traffic Psychol. Behav. 11, 83–95. https://doi.org/10.1016/J.TRF.2007.08.004.

Bierlaire, M., Chen, J., Newman, J., 2013. A probabilistic map matching method for smartphone GPS data. Transp. Res. C Emerg. Technol. 26, 78–98. https://doi.org/10.1016/J.TRC.2012.08.001.

Blondel, V.D., Decuyper, A., Krings, G., 2015. A survey of results on mobile phone datasets analysis. EPJ Data Sci. 4, 10. https://doi.org/10.1140/epjds/s13688-015-0046-0.

Blumenstock, J., Eagle, N., 2010. Mobile Divides: Gender, Socioeconomic Status, and Mobile Phone Use in Rwanda. In: Proceedings of the 4th ACM/IEEE International Conference on Information and Communication Technologies and Development - ICTD '10. ACM Press, New York, New York, USA, pp. 1–10. https://doi.org/10.1145/2369220.2369225.

Blumenstock, J.E., Gillick, D., Eagle, N., 2010. In: Who's Calling? Demographics of Mobile Phone Use in Rwanda. 2010 AAAI Spring Symp. Ser. AAAI Press.

Bwambale, A., Choudhury, C., Hess, S., 2017. Modelling trip generation using mobile phone data: A latent demographics approach. J. Transp. Geogr. https://doi.org/10.1016/j.jtrangeo.2017.08.020.

Calabrese, F., Di Lorenzo, G., Liu, L., Ratti, C., 2011. Estimating origin-destination flows using Mobile phone location data. IEEE Pervasive Comput. 10, 36–44. https://doi.org/10.1109/MPRV.2011.41.

Calabrese, F., Diao, M., Di Lorenzo, G., Ferreira, J., Ratti, C., 2013. Understanding individual mobility patterns from urban sensing data: a mobile phone trace example. Transp. Res. C Emerg. Technol. 26, 301–313. https://doi.org/10.1016/j.trc.2012.09.009.

Calabrese, F., Ferrari, L., Blondel, V.D., 2014. Urban sensing using Mobile phone network data: a survey of research. ACM Comput. Surv. 47, 1–20. https://doi.org/10.1145/2655691.

Chen, J., 2013. Modeling Route Choice Behavior Using Smartphone Data. Rep. TRANSP-OR.

Chen, C., Bian, L., Ma, J., 2014. From traces to trajectories: how well can we guess activity locations from mobile phone traces? Transp. Res. C Emerg. Technol. 46, 326–337. https://doi.org/10.1016/J.TRC.2014.07.001.

Chen, C., Ma, J., Susilo, Y., Liu, Y., Wang, M., 2016. The promises of big data and small data for travel behavior (aka human mobility) analysis. Transp. Res. C Emerg. Technol. 68, 285–299. https://doi.org/10.1016/j.trc.2016.04.005.

Çolak, S., Alexander, L.P., Alvim, B.G., Mehndiratta, S.R., González, M.C., 2015. Analyzing cell phone location data for urban travel. Transp. Res. Rec. J. Transp. Res. Board 2526, 126–135. https://doi.org/10.3141/2526-14.
Compaine, B.M., Kimmelman, G., 2001. The Digital Divide Confronts the Telecommunication Act of 1996, the Digital Divide: Facing a Crisis or Creating a Myth? MIT Press.
Danalet, A., Tinguely, L., Lapparent, M.d., Bierlaire, M., 2016. Location choice with longitudinal WiFi data. J. Choice Model. 18, 1–17. https://doi.org/10.1016/j.jocm.2016.04.003.
Davies, D.L., Bouldin, D.W., 1979. A cluster separation measure. IEEE Trans. Pattern Anal. Mach. Intell. PAMI-1, 224–227. https://doi.org/10.1109/TPAMI.1979.4766909.
Montjoye, Y.D., Smoreda, Z., 2014. D4D-Senegal: the second Mobile phone data for development challenge. arXiv Prepr.arXiv.
Delafontaine, M., Versichele, M., Neutens, T., Van de Weghe, N., 2012. Analysing spatiotemporal sequences in Bluetooth tracking data. Appl. Geogr. 34, 659–668. https://doi.org/10.1016/J.APGEOG.2012.04.003.
Demissie, M.G., Correia, G., Bento, C., 2013. Intelligent road traffic status detection system through cellular networks handover information: an exploratory study. Transp. Res. C Emerg. Technol. 32, 76–88. https://doi.org/10.1016/j.trc.2013.03.010.
Demissie, M.G., Correia, G., Bento, C., 2015. Analysis of the pattern and intensity of urban activities through aggregate cellphone usage. Transportmetrica A Transp. Sci. 11, 502–524. https://doi.org/10.1080/23249935.2015.1019591.
Diao, M., Zhu, Y., Ferreira, J., Ratti, C., 2016. Inferring individual daily activities from mobile phone traces: a Boston example. Environ. Plan. B Plan. Des. 43, 920–940. https://doi.org/10.1177/0265813515600896.
Frias-Martinez, V., Soguero-Ruiz, C., Frias-Martinez, E., Josephidou, M., 2013. Forecasting socioeconomic trends with cell phone records. In: Proceedings of the 3rd ACM Symposium on Computing for Development–ACM DEV '13. ACM Press, New York, New York, USA, p. 1. https://doi.org/10.1145/2442882.2442902.
Husain, W., Dih, L.Y., 2012. A framework of a personalized location-based traveler recommendation system in mobile application. Int. J. Multimed. Ubiquitous Eng. 7 (3), 11–18.
Iqbal, M.S., Choudhury, C.F., Wang, P., González, M.C., 2014. Development of origin–destination matrices using mobile phone call data. Transp. Res. C Emerg. Technol. 40, 63–74. https://doi.org/10.1016/j.trc.2014.01.002.
Järv, O., Ahas, R., Witlox, F., 2014. Understanding monthly variability in human activity spaces: a twelve-month study using mobile phone call detail records. Transp. Res. C Emerg. Technol. 38, 122–135. https://doi.org/10.1016/J.TRC.2013.11.003.
Jiang, S., Fiore, G. a, Yang, Y., Ferreira, J., Frazzoli, E., González, M.C., 2013a. A review of urban computing for mobile phone traces. Proc. 2nd ACM SIGKDD Int. Work. Urban Comput. - UrbComp '13 1. doi:https://doi.org/10.1145/2505821.2505828
Jiang, Z.-Q., Xie, W.-J., Li, M.-X., Podobnik, B., Zhou, W.-X., Stanley, H.E., 2013b. Calling patterns in human communication dynamics. Proc. Natl. Acad. Sci. U. S. A. 110, 1600–1605. https://doi.org/10.1073/pnas.1220433110.
Jiang, S., Ferreira, J., González, M.C., 2017. Activity-Based Human Mobility Patterns Inferred from Mobile Phone Data: A Case Study of Singapore. IEEE trans. BIG DATA 208–219.
Kamargianni, M., Polydoropoulou, A., 2013. In: Does Social Networking Substitute for or Stimulate Teenagers ' Travel ? Findings from a Latent Class Model. Int. Choice Model. Conf.
Kang, C., Liu, Y., Ma, X., Wu, L., 2012. Towards estimating urban population distributions from Mobile call data. J. Urban Technol. 19, 3–21. https://doi.org/10.1080/10630732.2012.715479.

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. https://doi.org/10.1371/journal.pone.0096180.
Lane, N., Miluzzo, E., Lu, H., Peebles, D., Choudhury, T., Campbell, A., 2010. A survey of mobile phone sensing. IEEE Commun. Mag. 48, 140–150. https://doi.org/10.1109/MCOM.2010.5560598.
Laurila, J.K., Gatica-Perez, D., Aad, I., J., B., Bornet, O., Do, T.-M.-T., Dousse, O., Eberle, J., Miettinen, M., 2012. The Mobile Data Challenge: Big Data for Mobile Computing Research, EPFL scientific publications.
Lee, H.J., Choi, J.Y., Park, S.J., 2005. Context-Aware Recommendations on the Mobile Web. Springer, Berlin, Heidelberg, pp. 142–151. https://doi.org/10.1007/11575863_30.
Leszczyc, P.P., Timmermans, H., 1997. Store-switching behavior. Mark. Lett. 8, 193–204. https://doi.org/10.1023/A:1007910503617.
Leszczyc, P.T.L.P., Sinha, A., Timmermans, H.J., 2000. Consumer store choice dynamics: an analysis of the competitive market structure for grocery stores. J. Retail. 76, 323–345. https://doi.org/10.1016/S0022-4359(00)00033-6.
Li, Z., Li, M., Wang, J., Cao, Z., 2011. Ubiquitous data collection for mobile users in wireless sensor networks. In: 2011 Proceedings IEEE INFOCOM. IEEE, pp. 2246–2254. https://doi.org/10.1109/INFCOM.2011.5935040.
Lian, D., Ge, Y., Zhang, F., Yuan, N.J., Xie, X., Zhou, T., Rui, Y., 2015. Content-aware collaborative filtering for location recommendation based on human mobility data. In: 2015 IEEE international conference on data mining. IEEE, pp. 261–270. https://doi.org/10.1109/ICDM.2015.69.
Liu, F., Janssens, D., Wets, G., Cools, M., 2013. Annotating mobile phone location data with activity purposes using machine learning algorithms. Expert Syst. Appl. 40, 3299–3311. https://doi.org/10.1016/j.eswa.2012.12.100.
Lu, X., Gu, X., 2011. The fifth travel survey of residents in Shanghai and characteristics analysis. Urban Transp. China 9, 1–7.
Lu, X., Pas, E.I., 1999. Socio-demographics, activity participation and travel behavior. Transp. Res. A Policy Pract. 33, 1–18. https://doi.org/10.1016/S0965-8564(98)00020-2.
McHugh, M.L., 2013. The chi-square test of independence. Biochem. Medica 23, 143–149. https://doi.org/10.11613/BM.2013.018.
Mokhtarian, P.L., 1990. A typology of relationships between telecommunications and transportation. Transp. Res. A Gen. 24, 231–242. https://doi.org/10.1016/0191-2607(90)90060-J.
Mokhtarian, P.L., 2003. Telecommunications and travel. The case for complementarity. J. Ind. Ecol. https://doi.org/10.1162/108819802763471771.
Mokhtarian, P., 2009. If telecommunication is such a good substitute for travel, why does congestion continue to get worse? Transport. Lett. 1, 1–17. https://doi.org/10.3328/TL.2009.01.01.1-17.
Molloy, J., Moeckel, R., Molloy, J., Moeckel, R., 2017. Improving destination choice modeling using location-based big data. ISPRS Int. J. Geo Inf. 6, 291. https://doi.org/10.3390/ijgi6090291.
Moschis, G.P., Ünal, B., 2008. Travel and leisure services preferences and patronage motives of older consumers. J. Travel Tour. Mark. 24, 259–269. https://doi.org/10.1080/10548400802156711.
Nobis, C., Lenz, B., 2009. Communication and mobility behaviour–a trend and panel analysis of the correlation between mobile phone use and mobility. J. Transp. Geogr. https://doi.org/10.1016/j.jtrangeo.2008.11.013
Ofcom, 2013. Communications Market Report. Ofcom.

Pappalardo, L., Simini, F., Rinzivillo, S., Pedreschi, D., Giannotti, F., Barabási, A.-L., 2015. Returners and explorers dichotomy in human mobility. Nat. Commun. 6, 8166. https://doi.org/10.1038/ncomms9166.

Pearce, K.E., Rice, R.E., 2013. Digital divides from access to activities: comparing mobile and personal computer internet users. J. Commun. 63, 721–744. https://doi.org/10.1111/jcom.12045.

Phithakkitnukoon, S., Horanont, T., Lorenzo, G.D., Shibasaki, R., Ratti, C., 2010. Activity-aware map : identifying human daily activity pattern using mobile phone data. In: Human Behavior Understanding. Springer, pp. 14–25. https://doi.org/10.1007/978-3-642-14715-9_3.

Phithakkitnukoon, S., Sukhvibul, T., Demissie, M., Smoreda, Z., Natwichai, J., Bento, C., 2017. Inferring social influence in transport mode choice using mobile phone data. EPJ Data Sci. 6, 11. https://doi.org/10.1140/epjds/s13688-017-0108-6.

Pinelli, F., Lorenzo, G.D., Calabrese, F., 2015. In: Comparing Urban Sensing Applications Using Event and Network-Driven Mobile Phone Location Data. Mob. Data Manag. (MDM), 2015 16th IEEE Int. Conf.

Qi, L., Qiao, Y., Abdesslem, F.B., Ma, Z., Yang, J., 2016. Oscillation Resolution for Massive Cell Phone Traffic Data. In: Proceedings of the First Workshop on Mobile Data - MobiData '16. ACM Press, New York, New York, USA, pp. 25–30. https://doi.org/10.1145/2935755.2935759.

Rahmati, A., Tossell, C., Shepard, C., Kortum, P., Zhong, L., 2012. Exploring iPhone usage: the influence of socioeconomic differences on smartphone adoption, usage and usability. In: Proceedings of the 14th International Conference on Human-Computer Interaction with Mobile Devices and Services - MobileHCI '12. ACM Press, New York, New York, USA, p. 11. https://doi.org/10.1145/2371574.2371577.

Rasouli, S., Timmermans, H., 2014. Activity-based models of travel demand: promises, progress and prospects. Int. J. Urban Sci. 18, 31–60. https://doi.org/10.1080/12265934.2013.835118.

Ratti, C., Pulselli, R.M., Williams, S., Frenchman, D., 2006. Mobile landscapes: using location data from cell phones for urban analysis. Environ. Plan. B Plan. Des. 33 (5), 727–748. https://doi.org/10.1068/b32047.

Rice, R.E., Katz, J.E., 2003. Comparing internet and mobile phone usage: digital divides of usage, adoption, and dropouts. Telecommun. Policy 27, 597–623. https://doi.org/10.1016/S0308-5961(03)00068-5.

Salomon, I., 1986. Telecommunications and travel relationships: a review. Transp. Res. A Gen. 20, 223–238. https://doi.org/10.1016/0191-2607(86)90096-8.

Salomon, I., 1998. Technological change and social forecasting: the case of telecommuting as a travel substitute. Transp. Res. C Emerg. Technol. 6, 17–45. https://doi.org/10.1016/S0968-090X(98)00006-0.

Sey, A., 2011. 'We use it different, different': making sense of trends in mobile phone use in Ghana. New Media Soc. 13, 375–390. https://doi.org/10.1177/1461444810393907.

Soto, V., Frias-Martinez, V., Virseda, J., Frias-Martinez, E., 2011. Prediction of Socioeconomic Levels Using Cell Phone Records. Springer, Berlin, Heidelberg, pp. 377–388. https://doi.org/10.1007/978-3-642-22362-4_35.

Srinivasan, K.K., Raghavender, P.N., 2006. Impact of mobile phones on travel. Transp. Res. Rec. J. Transp. Res. Board 1977, 258–267. https://doi.org/10.1177/0361198106197700130.

Thomas, S., Heinrich, S., Kühnlein, A., Radon, K., 2009. The association between socioeconomic status and exposure to mobile telecommunication networks in children and adolescents. Bioelectromagnetics 31, 20–27. https://doi.org/10.1002/bem.20522.

Thulin, E., Vilhelmson, B., 2007. Mobiles everywhere. Young 15, 235–253. https://doi.org/10.1177/110330880701500302.

van den Berg, P., Arentze, T., Timmermans, H., 2013. A path analysis of social networks, telecommunication and social activity–travel patterns. Transp. Res. C Emerg. Technol. 26, 256–268. https://doi.org/10.1016/J.TRC.2012.10.002.

van Deursen, A.J.A.M., van Dijk, J.A.G.M., ten Klooster, P.M., 2015. Increasing inequalities in what we do online: a longitudinal cross sectional analysis of internet activities among the Dutch population (2010 to 2013) over gender, age, education, and income. Telematics Inform. 32, 259–272. https://doi.org/10.1016/J.TELE.2014.09.003.

van Wee, B., Holwerda, H., van Baren, R., 2002. Preferences for modes, residential location and travel behaviour: the relevance for land-use impacts on mobility. Eur. J. Transp. Infrastruct. Res. 2, 305–316.

Wang, F., Chen, C., 2018. On data processing required to derive mobility patterns from passively-generated mobile phone data. Transp. Res. C Emerg. Technol. 87, 58–74. https://doi.org/10.1016/J.TRC.2017.12.003.

Wang, H., Calabrese, F., Di Lorenzo, G., Ratti, C., 2010. In: Transportation Mode Inference from Anonymized and Aggregated Mobile Phone Call Detail Records. IEEE Conf. Intell. Transp. Syst. Proceedings, ITSC. https://doi.org/10.1109/ITSC.2010.5625188.

Wang, Y., Correia, G., de Romph, E., Timmermans, H.J.P., 2017a. Using metro smart card data to model location choice of after-work activities: an application to Shanghai. J. Transp. Geogr. 63, 40–47. https://doi.org/10.1016/j.jtrangeo.2017.06.010.

Wang, Z., He, S.Y., Leung, Y., 2017b. Applying mobile phone data to travel behaviour research: a literature review. Travel Behav. Soc. 11, 141–155. https://doi.org/10.1016/J.TBS.2017.02.005.

Wang, Y., Correia, G., de Romph, E., Santos, B.F., 2018a. Road network design in a developing country using mobile phone data: an application to senegal. IEEE Intell. Transp. Syst. Mag. https://doi.org/10.1109/MITS.2018.2879168.

Wang, Y., Correia, G., van Arem, B., Timmermans, H.J.P.(.H.)., 2018b. Understanding travellers' preferences for different types of trip destination based on mobile internet usage data. Transp. Res. C Emerg. Technol. 90, 247–259. https://doi.org/10.1016/j.trc.2018.03.009.

Wesolowski, A., Eagle, N., Noor, A.M., Snow, R.W., Buckee, C.O., 2013. The impact of biases in mobile phone ownership on estimates of human mobility. J. R. Soc. Interface 10, 20120986. https://doi.org/10.1098/rsif.2012.0986.

Wolf, J., SchöUnfelder, S., Samaga, U., Oliveira, M., Axhausen, K., 2004. Eighty weeks of global positioning system traces: approaches to enriching trip information. Transp. Res. Rec. J. Transp. Res. Board 1870, 46–54. https://doi.org/10.3141/1870-06.

Yin, M., Sheehan, M., Feygin, S., Paiement, J.-F., Pozdnoukhov, A., 2017. A generative model of urban activities from cellular data. IEEE Trans. Intell. Transp. Syst. 1–15. https://doi.org/10.1109/TITS.2017.2695438.

Yuan, Y., Raubal, M., Liu, Y., 2012. Correlating mobile phone usage and travel behavior–a case study of Harbin. China. Comput. Environ. Urban Syst. 36, 118–130. https://doi.org/10.1016/J.COMPENVURBSYS.2011.07.003.

Zhang, M., Sawchuk, A.A., 2012. USC-HAD: a daily activity dataset for ubiquitous activity recognition using wearable sensors. In: Proceedings of the 2012 ACM Conference on Ubiquitous Computing–UbiComp '12. ACM Press, New York, New York, USA, p. 1036. https://doi.org/10.1145/2370216.2370438.