On Correlation between Mobile Phone Usage and Travel Behavior – A Case Study of Harbin, China

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1. Introduction

Information and communication technologies (ICTs), such as mobile phones and the Internet, are increasingly pervasive in modern society. These technologies provide more flexibility regarding when, where, and how to travel. Understanding the influence of ICTs in our current mobile information society will be essential for updating environmental policies, and maintaining sustainable mobility and transportation (De Souza e Silva 2007). Moreover, ICTs have provided a wide range of spatio-temporal data sources, which can be used in various areas of GIScience. Examples include geographic knowledge discovery and data mining in studies on geographic dynamics, such as human travel behavior and mobility patterns (Song et al. 2010; Yuan 2009).

Janelle (1995) introduced four types of communication modes based on different spatio-temporal constraints: Synchronous Presence (SP), Asynchronous Presence (AP), Synchronous Tele-presence (ST), and Asynchronous Tele-presence (AT). ICTs enhance the ability of tele-presence for human beings. However, the four communication modes interact with each other rather than being independent of each other. Therefore the development of ICTs also impacts physical movement of individuals in societies. Previous studies have focused on the interaction between ICT and human activity-travel behavior. Researchers recognized three main types of interaction: substitution, amplification, and synergy (Abler 1975; Mokhtarian and Meenakshisundaram 1999). However, due to the lack of sufficient data and the complicated nature of the interaction, there is still a continuing debate on how it works in everyday life. Some scholars are skeptical of simple and universal conclusions of how ICTs affect daily activities (Kwan et al. 2007). Couclelis (2004) described the fragmentations and regrouping of daily activities in the age of instant access. Moreover, substantial differences in the use of mobile technology exist, resulting from many social factors, including age, gender, culture, and socioeconomic distribution. Therefore, the influence of population heterogeneity should be taken into account in this research question. This aspect has not been fully addressed in existing research.

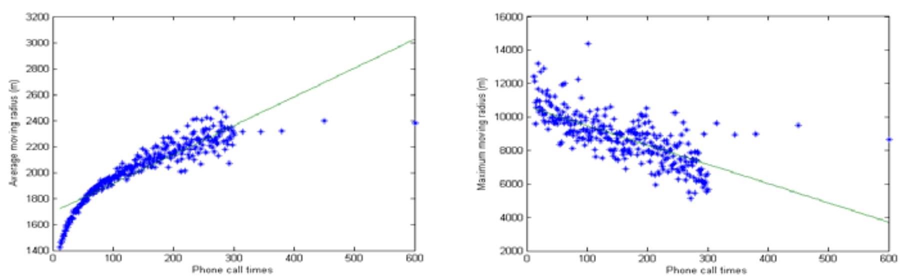
In this research, we focus on examining how population heterogeneity impacts the relationship between mobile phone usage and individual activity behavior based on a dataset from Harbin City, China. We propose to account for the heterogeneity of the population when analyzing the correlation between ICT and human activity-travel behavior. As a result it is important to specify individual attributes (e.g., cultural, social, institutional, physical aspects) when investigating this problem. It is highly possible that mobile phone usage and travel behavior correlate differently among various social groups. Therefore, a general conclusion for the population is insufficient to represent the complicated nature of this question. Since the results of the current analysis told us little about causality, the term “relationship” in this research refers to correlation rather than causality.

2. Data and pre-processing

Harbin city is a major commercial, industrial, and transportation center situated in northeast China. It was ranked as one of the top ten populated cities in China in the year 2009. The dataset covers over one million people from Harbin city, including mobile phone connection records for a time span of 9 days. The data include the time, duration, and location[1] of mobile phone connections, as well as the age and gender attributes of the users. Note that the location records in the dataset cannot represent the accurate moving trajectory of each user, since the locations are recorded only when there is a phone call connection. However, based on a summary of 9 days’ records, the data are still useful for depicting the general characteristics of individual travel mobility. Therefore, for each individual, we approximated the physical movement area based on the rotation of user trajectories (Gonzalez et al. 2008). The radius of gyration was considered as a measurement of moving radius.

3. Methodology and preliminary results

To test the hypothesis, first the whole dataset is divided into groups according to the frequency of mobile phone usage, and then the average/maximum movement radius is calculated for each group. The correlation between phone usage and movement radius is investigated using linear regression. The results of the data analysis show a significant positive correlation between mobile phone usage and average movement radius (Figure 1a), whereas a negative correlation between mobile phone usage and maximum movement radius is demonstrated (Figure 1b). The contradiction indicates that, even though we can generally conclude that mobile phone usage is positively correlated to physical movement, this conclusion is not comprehensive for explaining the entire problem.



(a) (b)

Figure 1. The correlation between mobile phone usage and movement radius. (a) average movement radius; (b) maximum movement radius.

To further explain the contradiction, we extract four groups with different frequencies of mobile phone usage and analyze the distribution of individual movement radii in each group. Figures 2 (a) (b) (c) (d) represent the histograms of movement radii for the four groups (the frequency of mobile phone calls = 10, 50, 100, 200 respectively). As

[1] For each user, the location of the nearest cell phone tower is recorded both when the user makes and receives a phone call. The data accuracy is about 300m-500m.

shown in Figure 2, when the frequency of mobile phone connections increases, we have the following statistical results:

(1) The average movement radius increases.
(2) The standard deviation of movement radius decreases.
(3) The maximum movement radius decreases.

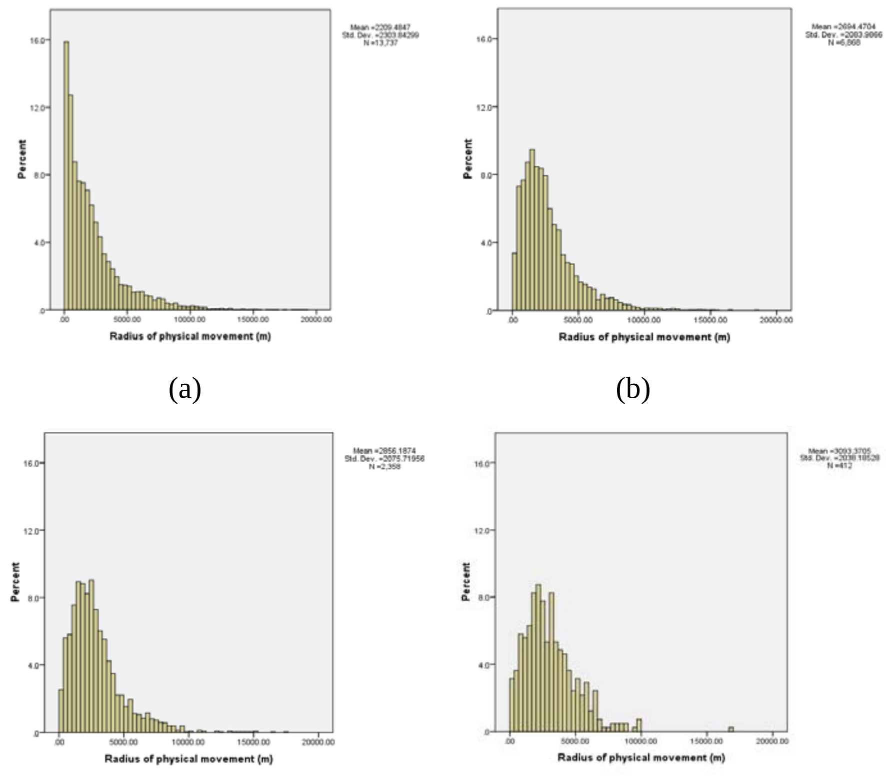


Figure 2. Histogram of movement radius for groups with difference phone usage. (a) phone calls = 10; (b) phone calls = 50; (c) phone calls = 100; (d) phone calls = 200.

Moreover, further analysis indicates that the distribution of age represents a similar pattern as the histograms of movement radii in Figure 2. Therefore, we can also conclude that the standard deviation of age decreases when mobile phone usage increases.

The results above can be interpreted from two perspectives. First, since the average movement radius increases as mobile phone usage increases in both Figure 1 and Figure 2, we can generally conclude that mobile phone usage is positively correlated to movement radii. Second, for groups with fewer phone calls, the population heterogeneity is more significant due to the higher standard deviations of age and movement radius. Therefore, the groups with fewer phone calls correspond to a larger variety of phone users. People with more phone calls also have a more homogeneous social background. This also explains the negative correlation between maximum movement radius and mobile phone usage. The groups with a larger population variety are more likely to have a large range of movement radius and more extreme values of movement radius, so the maximum values are declining as the population heterogeneity declines.

4. Future work

This research provides us with new insights regarding the study of correlation between ICTs and travel behavior. As indicated in the preliminary results, ICT data (e.g., mobile phone datasets) offer new resources for geographic knowledge discovery and achieving inferential spatio-temporal information in the age of instant access, both important research areas in GIScience. Our future research will focus on data mining and knowledge discovery based on mobile phone usage information, such as analyzing the correlation between phone usage and trajectory patterns. This would provide more specific results on how mobile phone usage impacts an individual's movement pattern, as well as offering references to policy makers. In addition, we will work on generalizing the results to other cities, as well as the comparison among cities with various social, political, and cultural backgrounds.

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