Changing mobility through health information on the mobile Internet

Marina Laube

MSc in Social Science of the Internet
Green Templeton College

Thesis submitted in partial fulfilment of the requirement for the degree of MSc in Social Science of the Internet at the Oxford Internet Institute at the University of Oxford

August 2012
10,000 words

Abstract

The effects of the mobile Internet on our everyday lives are still largely unexplored. Providing access to information anywhere and anytime, its implications on our mobility—as suggested by domestication theory—are significant. This thesis attempts to close knowledge gaps concerning the relation of the mobile Internet to everyday mobility. I shall argue that the mobile Internet distinguishes itself from other media in its ability to cope with spatio-temporally fast changing information and can therefore provide more relevant data as a basis for decision-making processes on travel and health behaviour. The focus will be on the dissemination of air quality information, which is characterised by its spatial and temporal variability. The research questions asked follow the goal of determining whether air quality information leads to changes in mobility, in what forms these changes occur and which other factors are relevant. A survey conducted among users of the London Air application collects data on users' mobility behaviour, their amount of app use as well their health condition and other explanative variables.

In a first explorative, analytical approach, three different mobility components are derived before being used as dependent variables in the subsequent analysis. The following hierarchical regression and the discussion of the findings reveals that users do indeed change their mobility based on air quality information provided by the app, although changes are conducted seldom and the explained variance by app use is small. In conclusion, this study confirms findings from similar studies which find that subjective awareness of air pollution leads to more behavioural changes than air quality advisories. Furthermore, this paper suggests that the mobile Internet complements other media but has greater relevance when used outside of the home. Finally it is suggested that future research use GPS data to increase the accuracy of the findings and additionally incorporate other effects apart from mobility changes as possible effects of the mobile Internet.

Acknowledgements

First and foremost I would like to thank my supervisor, Dr Grant Blank, for his constant support and guidance throughout the last year. His broad knowledge and advice have been tremendously instructive.

I also wish to thank the Environmental Research Group of King's College London who supported this research by allowing me to conduct my data collection on the London Air application. Special acknowledgement is due to Andrew Grieve who was extremely helpful by reviewing the survey and updating the London Air app.

Finally, my gratitude goes to Green Templeton College for a learning grant covering part of the costs related to the update of the London Air application.

Contents

List of Tables

1. INTRODUCTION

The mobile Internet allows access to information anytime and anywhere. This aspect is especially relevant regarding spatio-temporal data and in particular health-related subjects where location and time correlate with the strength of health impacts (Bøhler et al. 2002; Resch et al. 2011). Stakeholders rely on receiving this information fast and in an appealing form, thus allowing them to make better decisions, adjust their behaviour and stay healthier in the long term (Bøhler et al. 2002; Kelly et al. 2012). The current literature does not consider the mobile Internet as a distinctive dissemination channel for health information and neglects to analyse behavioural changes and their long-term impacts based thereon. Thus, the present paper seeks to consider the spatio-temporal extension of the Internet as established through mobile phones, arguing that the availability of spatio-temporally changing information anywhere and anytime increases its relevance and therefore its likelihood to affect people's behaviour. The focus is on air quality information and citizens' mobility, which—based on the suggestions of domestication theory (Haddon, 2004)—serves as an indicator for changes in people's everyday behaviour as determined by information and communication technology (ICT). The main questions to be addressed include whether and how the mobile Internet contributes to changes in mobility when information on air quality can be accessed anywhere and anytime. Discussion also focuses on the potential impact of these changes on mobility in urban environments, public health, and the mobile Internet itself. A survey is conducted among users of the London Air app, a smartphone application which provides almost real-time air quality data at street level in London. The findings suggest that there is a significant relationship between the perception of air quality information and changes in mobility, but that despite the high awareness of adverse health impacts caused by air pollution among the app users, only a minority actually make these changes. Furthermore, alternative explanations for mobility changes are found and possible explanations given for a lack of change. Limitations to these findings result from the use of a cross-sectional study design, the sampling procedure, and biases in the self-reporting of users' behavioural changes. However critically assessed, the outcomes constitute a valuable basis for further research on the dissemination of data on the urban environment as well as its use for behavioural changes and health protection.

The remainder of the paper is organised as follows. The next section contains a review of the related theories and approaches in the chosen field of study. Subsequently methods and their implications are presented, followed by the compilation of collected data and the results of their analysis. Finally the findings are discussed and answers to the research questions given, prior to a general conclusion.

2. THEORETICAL CONTEXT

Location-related health-information on the mobile Internet and its impacts on our daily mobility as well as, more generally, our interactions with the urban environment is a subject involving manifold disciplines. As such, there are several approaches that constitute the overall theoretical background. This section aims to synthesize established fields of research that can be pieced together in order to establish an area of knowledge around mobility, the mobile Internet, and location-related health information.

2.1 ADVERSE HEALTH IMPACTS OF AIR POLLUTION

The necessity to provide environmental information to the public arises through the adverse impact that air pollution has on our physical health. As referred to by the London Air Quality Network, air pollution is defined as the release of particles and noxious gases into the atmosphere which have an effect on human health (LAQN, 2012). The current UK air quality index takes the following pollutants into account: ozone (O_3), nitrogen dioxide (NO_2), sulphur dioxide (SO_2), particulate matter of less than 10μm in diameter (PM_{10}) and particulate matter of less than 2.5μm in diameter ($PM_{2.5}$) (COMEAP, 2011).
Health implications of individual pollutants have been widely documented (Gauderman et al. 2004; Schildcrout et al. 2006; Amann et al. 2008; USEPA, 2011). Even a brief daily exposure to emissions from road vehicles, planes and powerplants can lead to respiratory problems (Delfino et al. 1998; Kumar et al. 2011). In the long term, air pollution increases cardiovascular and pulmonary diseases (Dominici et al. 2006; Rosenlund et al. 2006; Liang et al. 2009; Stieb et al. 2009; Strickland et al. 2010), morbidity and mortality (Kelly et al. 2012), and may even negatively affect reproduction as well as neurological health (Dales et al. 2009; Darrow et al. 2009). A recent study conducted by Yim and

Barrett (2012) was able to quantify the negative effects of air pollution in the UK. By analysing the long-term exposure to particulate matter ($PM_{2.5}$ and PM_{10}), the authors make an estimate of 13,000 premature deaths per year caused by combustion emissions. Specifically related to London, where concentrations of particulate matter are the highest in the UK, the authors expect 3,200 air-quality related deaths annually.

However, health effects of air pollution and susceptibility to it may vary between individuals and according to their health condition, age or extent of exposure (Kelly et al. 2012). Other affecting factors include the amount of outdoor physical activity, cardiovascular and respiratory diseases, their severity and whether medication is taken for them (Delfino et al. 1998; Kelly et al. 2012). Although people usually experience a broad range of different air quality environments on a daily basis (Holloway et al. 2005), long-term variations in the exposure between individuals seem to balance out (Schlink et al. 2010).

2.2 Air pollution data as information

The variability of air pollution in terms of location, time and health effects adds significantly to the complexity of its measurement, calling for sensor networks capable of collecting and providing information in real-time (Bøhler et al. 2002; Resch et al. 2011). The accuracy of air pollution data is an important condition for the increase of public health and our general understanding of the city and its impacts on society (Boulos, 2004; Resch et al. 2011). First, these measurements of environmental information act as a basis for citizens to protect themselves from adverse health effects (Kelly et al. 2012) as long as the information is provided quickly, efficiently and is easy to understand (Bøhler et al. 2002). Second, city authorities and national governments are provided with a solid base upon which to decide on political actions to ensure air quality standards and decrease future air pollution, as well as measuring the cost effectiveness of prior actions (Boulos, 2004). Third, collected data can be used in models to forecast air quality appropriately and alert the population (Bøhler et al. 2002; Kelly et al. 2012). Finally, data on air quality increases citizens' responsiveness towards environmental issues and raises the general environmental consciousness, which is necessary for a free exchange of opinions as well as more effective public participation in environmental decision-making (Hipólito, 2007). All these needs for accurate environmental data follow the overall goal of initiating changes in individual behaviour and public policy in order to attain a cleaner environment and a healthier population (Kelly et al. 2012). Citizens expect this information to come in a form easy to understand, indicating pollution levels and locations, and which includes advice on how they should react (COMEAP, 2011). This need is further accompanied by legal requirements on the measurement, collection and dissemination of air quality data. Thus, the UK is obliged to follow the EU air quality policy, outlaid in Directive 2008/50/EC[1] on ambient air quality and cleaner air in Europe (European Union, 2008). The provision states explicitly that up-to-date information must be made available on a regular basis, free of charge, in a clear and comprehensive manner and via easily accessible media. Regarding the latter, in the UK email services, websites, mobile text messages, voicemail, a public phone service and smartphone applications[2] are used. The information itself may consist of spatial and temporal air quality and emission data (e.g. concentrations and deposition rates), air quality forecasts, measures to decrease

---

[1] This directive was made law in England through the Air Quality Standard Regulations 2010 which oblige the Department for Environment, Food and Rural Affairs (Defra) to report air quality data on several air pollutants. These are: sulphur dioxide, nitrogen dioxide, oxides of nitrogen, particulate matter, lead, benzene, carbon monoxide, arsenic, cadmium, mercury, nickel, benzo(a)pyrene or other polycyclic aromatic hydrocarbons, ozone (European Union, 2008).

[2] Most air pollution alert services combine several means of providing information to the public and are therefore not distinguishable by medium. Further information and access to alert services can be found here: http://uk-air.defra.gov.uk, http://www.airtext.info/ and http://www.londonair.org.uk/

personal exposure, guidelines for vulnerable sections of the population and administrative details (Bøhler et al. 2002; Air Quality Standard Regulations, 2010).

2.3 The mobile Internet and environmental information

The number of mobile phone subscriptions related to the worldwide population reached 86.7% by the end of 2011, indicating that mobile phones have become the most widely adopted ICT worldwide (International Telecommunication Union, 2011). Being capable of accessing information and services at different times and places, the disconnected space-time relationship becomes the mobile phone's distinguishing feature (Huomo, 2001; Alexander et al. 2011). Whereas Bøhler et al. (2002) assess this attribute as a loss in the importance of place because people seeking information can access it wherever they are, I shall argue instead that place becomes significant when related to spatio-temporally changing information. This kind of information is especially relevant at a specific place and time, for instance in the form of air quality data or traffic reports, which both play a major role in mobile contexts. As Berry and Hamilton (2010) state, mobile phones are increasingly crucial for our mobility. Especially with smartphones as a subgroup of mobile phones distinguished by their multi-functionality—combining access through the Internet anytime and anywhere to spatio-temporally changing information, with the spatial context of their users detected by geographic positioning system (GPS)—, this proposition can be strongly supported. Offering us constant access to the collected data on our environment, the mobile phone acts as a sixth sense (Mistry, 2012) leading to a changing perception of space (De Souza e Silva, 2006). Its additional capacity of producing spatiality by facilitating our movement and detecting our mobility (Wilson, 2012) support its suitability for spatio-temporally changing information. Combined, these features meet the complex requirements of air pollution dissemination as they are able to take its spatial as well as its temporal variability into account and provide real-time, location-related health information wherever and whenever needed. The London air application[3] is such an alert service that proactively provides measurements of the air quality in London and gives health advice related to measured air pollution levels (Kelly et al. 2012). As it requires access to the mobile Internet when run on smartphones and disseminates health information people can react to in mobile contexts, it is very useful for my research and will play a major role in this study.

2.4 Domestication Theory

Originally situated in anthropological, cultural and consumption studies (Hjorth, 2009), domestication theory was developed into an interdisciplinary framework by Silverstone et al. (1992), who applied it to several ICTs by contrasting it with their precursors who had focused on traditional media such as television and the telephone (e.g. Hobson, 1980; Bausinger, 1984; Lull, 1988). Key elements addressed by the theory are the way new ICTs enter private homes, concomitant social processes, the functions ICTs assume, and their symbolic aspects (Silverstone et al. 1992; Silverstone and Haddon, 1996). The authors distinguish four basic processes when a household acquires a new object: appropriation, objectification, incorporation and conversion. They illustrate how a new technology is integrated into one's home, establishes itself as part of one's daily routines, how it interacts with one's life and also how it affects the use and choice of technology (Røpke, 2001; Haddon, 2007). Therefore domestication theory can be identified as part of Social Constructionism which 'positions technology as having the power to impact

[3] Further information on the London Air app can be found on the website of the London Air Quality Network (http://www.londonair.org.uk/LondonAir/MobileApps/, 31st July 2012) and in the Apple app store (http://itunes.apple.com/gb/app/london-air/id358970517?mt=8, 31st July 2012).

upon everyday life, but also constructs technologies as the result of social processes' (Green, 2010, p.9).

Although initially related to the incorporation of ICTs at home, domestication theory is also applicable to mobile contexts and the analysis of the ubiquity of the mobile Internet in our everyday lives (Hjorth, 2009), as reflected by its high distribution[4] in the UK. Drawing on the early attempts of Lie and Sørensen (1996), Haddon (2004) expanded domestication theory by considering the relation of ICTs and public spaces. Thus, ICTs were identified by him as both being affected by changes in mobility, and as themselves affecting the experience, organisation and patterns of travel, for instance by providing us with information on our surroundings. Specifically referring to the mobile Internet, Green and Haddon (2009, p.149) state that it 'might be shaped by and influence different spaces'. These suggestions are supported by Kwan (2006) who sees changes in people's use of time, the increased spatial and temporal flexibility of daily activities and travel as well as the increased geographical mobility as results of mobile communication (Kwan 2002; Kwan 2006). Kopomaa (2000) expects people to spend more of their free time outside, Graham and Marvin (1996) that they will use urban spaces more flexibly, and Kenyon et al. (2002) see the strength of mobile communication in its virtual mobility as enhancing accessibility for people who are physically restricted. In summary, Kwan (2006) stresses the occurrence of new behavioural and spatial patterns effected by the mobile information age. Following Kelly et al. (2012) who point out that the aim of monitoring air pollution should be to empower people to modify their own behaviour, this study applies domestication theory to the mobile Internet in order to draw conclusions about its impacts by measuring behavioural changes. Thus, users of the London Air app would

[4] 45% of all Internet users employed a mobile phone to connect to the internet in 2011 (ONS, 2011).

presumably make decisions and change their behaviour to protect their health in response to notifications received through the app.

2.5 Behavioural changes

The principal proposition of the behaviourist school mainly developed by Pavlov (1897), Thorndike (1905), Watson (1913) and Skinner (1938) is that human actions are behaviours that can be altered by the environment. Based on the work of these authors, Bandura (1978) established the concept of reciprocal determinism and developed his ideas into social cognitive theory (Bandura, 1986) in which he reconceptualises individuals as self-organising, proactive, self-reflexive, and self-regulating. Together with Ajzen's (1985) theory on planned behaviour, Prochaska's and DiClemente's (1986) model of change as well as Becker's (1974) health belief model, Bandura's (1986) social cognitive theory formed the foundation of conceptual models on behavioural change that have been applied across different disciplines. These approaches are relevant to this thesis as they emphasise the ways in which people's decisions on behaviour are made in daily life. Moreover they can be applied to both health as well as mobility behaviours, which interact with each other when related to air quality information since health outcomes depend on changes in mobility. These are defined through variation in location, duration, frequency, sequence, distance and travel time (Ren and Kwan, 2009) and will be understood as a response to the provided health information (Kelly et al. 2012).

Prior studies of behavioural changes to some extent considered environmental information online, health decisions, subsequent changes in mobility or resulting health outcomes as a subject, but never analysed all of these aspects taken together. A study by Fjeldsoe et al. (2009) found that SMS-delivered interventions have positive short-term behavioural implications, but neither related to spatio-temporally changing data nor measured behavioural outcomes in terms of changes in mobility. Another paper by

Semenza et al. (2008) specifically analysed the effects of air pollution information on behavioural changes, but also without considering the mobile Internet as a source of information. Their results indicated that awareness of air pollution exists but that only 10–15% of all participants change their behaviour and that subjective perceptions of air quality have higher impacts on behavioural changes than air quality advisories. Other findings suggest that behavioural changes based on air quality information primarily occur when they reach susceptible groups who are at higher risk of adverse health effects, but they too did not take into account the mobile Internet as a medium of dissemination (Wen et al. 2005; McDermott et al. 2006; COMEAP, 2011). In general it seems that studies on health interventions are either not capable of proving positive outcomes of health interventions (Halko and Kientz, 2010) or that effects of health information on behaviour are predominantly low (McDermott et al. 2006; COMEAP, 2011; Kelly et al. 2012).

Literature on mobility behaviour can be traced back to Simon (1959) and Pred (1967) as early examiners of decision-making processes in empirical contexts. Later, behaviourism gained further importance in geography as Ajzen's (1991) theory of planned behaviour was included and applied to decision-making mobile contexts (McCormack and Schwanen, 2011). This resulted in a range of travel studies (Timmermans and Golledge, 1990; Timmermans et al. 2002; Dijst et al. 2008;) and the emphasis on location as being crucial for decision-making processes (Kahnemann, 2003; Adey and Anderson, 2011; Middleton, 2011). Finally Hitchings (2011) and Middleton (2011) understood decision-making as being embedded beyond the location in everyday life, but until now there were no studies that explored the mobile Internet and its information as a determining factor of mobility, although the mobile technologies themselves are acknowledged to have the capacity of reconfiguring everyday movement (Aguiléra et al. 2012; Wilson, 2012). The latter is confirmed by a broad range of studies on the implications of ICTs in general on our mobility—instead of on the information provided by them (e.g. Salomon, 1986; Mokhtarian and Meenakshisundaram 1999; Dijst, 2004; Haddon, 2004; Kwan, 2002; Kwan et al. 2007; Yoshii and Sasaki, 2010). However, these examples as well as papers on the effects of the Internet (e.g. Mokhtarian et al. 1995; Bagley and Mokhtarian, 1997; Gould and Golob, 1997; Mokhtarian and Salomon, 1997; Balepur et al. 1998; Golob and Regan, 2001; Ferrell, 2005; Ren and Kwan, 2007; Farag et al. 2007; Goodchild and Carley, 2010) do not fully cover the subject of my investigation, since up-to-date and location-related health information as mobile Internet content is not taken in account. The shift towards location occurring across the Internet (Wilson, 2012), neogeography (Graham, 2010) as well as its impact on physical mobility are still rarely explored (Line et al. 2011).

2.6 Research Questions

Although mobile technology and the Internet have been proven to impact mobility and it has been shown that health information can lead to behavioural changes, there is no study that combines these subjects in order to examine the effects of mobile air quality information on people's mobility. Further investigations are therefore necessary and especially justified for the following reasons: (1) The mobile Internet may offer citizens a better basis for decision-making than other ICTs because it can cope with spatio-temporally changing information. (2) The convenience and accessibility of the information may increase the likelihood of behavioural changes. (3) Behavioural changes can enhance public health and feed back into our use of technology, public awareness of the environment, the perception and experience of space, and finally alter social norms (Røpke, 2001; Höflich 2005a and 2005b; Hipólito, 2007; Aguiléra et al. 2012).

This paper extends the existing literature through the assessment of mobile access to air quality information on health behaviour and particularly mobility. In terms of domestication theory, behavioural approaches and current literature on ICTs and mobility, the question to be answered is how the mobile Internet changes our everyday activities, our health behaviour and our urban mobility. The main research question this study therefore seeks to answer is:

Do users of the London Air application change their mobility based on air quality information available through the app?

From this general research question two specific sub-questions have been derived which shall be discussed and answered.

R1. **Do users of the London Air app perceive changes in their everyday mobility based on air quality information provided by the app? Are the implications of air quality information reflected in the means of transport they use or the route, time, frequency, and organisation of mobility?**

R2. **Does the impact of air quality information on mobility changes vary by: the normal means of travel of the study participants, their amount of hours spent outside and especially the amount of time being outdoors while involved in physical activities, their use of additional information sources, their health condition, their awareness of air pollution and health symptoms they expect as being due to air pollution, age or gender?**

While the first question (R1) reflects the goal of examining whether changes take place at all and whether they can be determined via the aforementioned mobility aspects, the second question (R2) aims to monitor additional influences which might affect the main relation of air quality information and mobility changes. The next chapter explains the methodology used for collecting the necessary data to answer these queries.

3. METHODS

By choosing positivism as an epistemological paradigm, the research at hand believes in a phenomenalistic reality which considers knowledge to be derived through experiencing the world (Kolakowski, 1972; Marsh, 2002). Deductive and inductive approaches, which can both be part of positivism (Bryman, 2008), ensure its applicability to the little explored field of the subject of this study and allow for the testing of ideas derived from theory as well as for the establishment of new relations between variables from the collected data. The research methods used to this end may either be quantitative or qualitative, and both are found in the current literature. Although domestication studies prefer to use the latter (Haddon, 2007), I decided to conduct a quantitative study in order to quantify the assumed relationship (Babbie, 2010) between *air quality information* and *mobility changes* and test for coherence between these constructs. Finally, temporal restraints determined a cross-sectional design that limits the inferences to one point in time (de Vaus, 2002) and further abandons temporal group comparisons.

3.1 RESEARCH DESIGN

In order to fulfil the goal of gaining the necessary data to assess the impacts of air quality information on people's mobility, I decided to choose a method capable of capturing mobility changes explicitly determined by air quality information and meeting the settings outlined above. The derived suitability of a survey can be reflected in several aspects. First, surveys do not require control groups because variation is expected to occur naturally (de Vaus, 2002). Inferences are therefore made through comparisons within one group of participants (Marsh, 2002). Second, surveys allow capturing quantitative data on complex concepts: on the one hand by operationalising concepts into items in single queries (Bryman, 1984), on the other hand by measuring social phenomena with scales (Bulmer, 2001). Third, considering limitations, a survey can prove the assumed causality between concepts by asking the participants specifically about mobility changes determined by air quality information. Biases through self-declaration are minimal because changing mobility is a conscious decision-making process and the related questions will therefore be specific and familiar to the participants (Warwick and Lininger, 1975). Moreover, this approach is less extensive than the case studies usually conducted for domestication or mobility research, but more explicative than studies based on pure metrics. Finally, the decision to conduct the survey online in the form of a fill-out questionnaire has further advantages, such as cost-efficiency, self-management, easy access to the questionnaire, no bias through the interviewer, and a digital data collection (Hewson and Laurent, 2008; Vehovar and Manfreda, 2008). Overall these advantages of the online survey have to be weighed carefully against the efforts required to link the survey to the London Air application. Although this approach allowed getting very close to the participants of my sample and offered them to participate anytime and anywhere, there were also limitations, as will be further elaborated below.

3.2 Concepts and operationalisation

Deduced from the research questions, *mobility changes* are seen as a consequence of the consultancy of *air quality information* on the mobile Internet. For their measurement both terms had to be operationalised as they constituted too general constructs (Punch, 2005).

Looking first at *air quality information,* one must take into consideration that the availability of information does not guarantee its perception. Further *air quality information* might be updated several times a day as well as disseminated by different media. In the questionnaire participants will therefore have to indicate how often they use the London

Air app, whether they check air pollution levels several times a day and finally, whether they are using other information sources to access information about air quality. These three indicators can then be taken together to decide on someone's perception of *air quality information.*

The measurement of *mobility changes* was divided into two dimensions. The first dimension related to people's attitudes and likelihood to make changes in their mobility behaviour (Alwin and Krosnick, 1991). Their agreement or disagreement with five selected statements regarding mobility changes has been collected with a five-item Likert scale (Oppenheim, 2000). The second dimension measured the frequency of how many mobility changes had actually been made in reference to the same five mobility aspects which had been queried in the attitude questions and which were: (a) decisions on going outside, (b) planning and organisation of outdoor activities, (c) choice of travel route as well as (d) choice of time to go outside and (e) the means of travel (Ren and Kwan, 2009; Kelly et al. 2012). Combined, these aspects determined a multiple-indicator scale for the concept of *mobility change* (Hardy and Bryman, 2009).

Beside the assumed relation of *air quality information* and *mobility change*, several control variables had been considered in order to ensure the internal validity of the study (Punch, 2005). Based on the literature available it was expected that the amount of time spent outside, health condition, demographic aspects and awareness of adverse health effects due to air pollution might explain some variance of the dependent variable (Punch, 2005). Additionally the regularly used means of travel, self protection from air pollution and the context of the decision-making process have been considered as control variables[5]. In order to enable comparability, frequency questions were all assigned the same number of response alternatives and were collected in ordinal scales (Gaskell et al. 1994). Overall the

[5] See Appendix 1 for the questionnaire and an overview of all variables.

questionnaire included 25 questions and was pretested with four people using either an iPhone or an Android smartphone.

3.3 Sampling

In accordance with the lack of an exhaustive list of all air quality information receivers in the UK that could have been used for a random sample (Austin, 2002) and the expected low distribution of air quality information receivers in the general population, this study focuses on a population very likely to perceive air quality information by taking a convenience sample (Fricker, 2008) of the London Air app users. The population has been estimated to include 4'671 people who updated the app to the new version with the survey and who represent about 80% of all original app downloads. However, these quantities have to be assessed carefully because the app can be deleted and downloaded by the same user several times and downloading or updating the app does not determine its usage.

Although there was no statistic on the number of users who regularly accessed the app and would therefore receive an invitation to participate in the survey, a response rate of 15% (MacElroy, 2002) was expected. At least 280 responses were required to achieve a statistical power of 0.8 and an alpha level of 0.05 (Bryman and Cramer, 1994).

3.4 Data Collection

For the data collection I collaborated with the Environmental Research Group at King's College London who had developed the London Air app and agreed to support my project. With the help of King's, the app was updated in two aspects. First, a pop-up was installed which was activated at the launch of the app and invited the user to take part in my survey. Second, the app was updated with the capability to start the smartphone's browser and automatically open the link to the survey as soon as a user decided to participate. I developed the web-based survey with the help of WebSurveyCreator[6], an online survey software which offers predefined layouts applicable to smartphone browsers. Using this service accelerated the implementation process since only minor technical skills had to be acquired. Starting on 5th June 2012, data was collected for 37 days until 11th July 2012. In this time span 70 complete responses were collected, each of which constituted a case in my study. As response rates were low, the duration of data collection was extended beyond the initially planned four weeks as a strategy of reducing non-response (Bryman, 2008).

3.5 Implications

The chosen study design, research method and mode of data collection is mirrored in several implications relevant to the ethics, quality, analysis and conclusions of this study. The research was conducted in compliance with the ethical guidelines of the Social Research Association (SRA, 2003) and approval of the Central University Research Ethics Committee (CUREC)[7]. Users of the London Air app were extensively informed on the goal of the study and were asked to give their prior consent in order to participate in the survey. With respect to their privacy all participants were guaranteed anonymity and secure data storage, especially since some of the questions related to their health condition and were therefore sensitive.

The quality of a study can be assessed by its validity and reliability (Kidder, 1981; Babbie, 2010). Although validity is secured through focused questions derived from theory, as yet

[6] http://www.websurveycreator.com/ (31st July 2012)
[7] http://www.admin.ox.ac.uk/curec/ (31st July 2012)

not all items used have been proven to represent the underlying concept and further assessment regarding their relevance will be required in the analysis. The consistency of the measuring instrument, referred to as reliability (Punch, 2005), was given, with the exception of the frequency questions likely to lead to other outcomes when repeated. A major number of implications was due to the choice of a survey as a mode of data collection. Marsh (2002) for instance insists that observations made in surveys might not reflect reality and too strongly influence participants' answers. Inability of measuring meaningful aspects and contexts on the one hand and cognitive negligence on the other must also be taken into consideration (de Vaus, 2002). Participants in my survey were further expected to differentiate between *mobility changes* due to *air quality information* and *mobility changes* due to other reasons which might have led to a self-reporting bias, thereby limiting the causality of measuring (Judd and Kenny, 2006). These implications are part of the general limitations of the study design, which may lead to false inferences and inability to prove temporal causality (Stouffer, 2002; Marsh, 2002). All these restraints as well as possible biases through the non-random sample (Sudman and Blair 2002; Austin, 2002) and the low response rate (Punch, 2005) will have to be taken into account in the analysis and interpretation of the results.

4. Data analysis and findings

The collected survey data of 70 cases was exported into STATA11 for analysis. After assigning values to all observations by recoding the variables[8] (Knoke et al. 2002), statistical methods were applied to the data. The objective of the analysis was primarily to extract the associations necessary for answering the research questions. Thus the relation between *air quality information* and *mobility changes* was analysed regarding correlations, patterns and the influence of control variables. The results gained in this process and presented in this chapter serve as a foundation for the discussion of whether and how variations in mobility behaviour can be explained by the perception of air quality information and which further aspects influence this relationship.

First, characteristics of the set of cases were analysed (de Vaus, 2002), with the purpose of identifying missing values, outliers or non-consistent answers in the data (Bryman and Cramer, 1994). Then the focus shifted towards the main constructs of *air quality information* and *mobility changes*. In terms of an explorative evaluation and with the help of Cronbach's alpha (Cronbach, 1951), the reliability of the considered items was examined. This was followed by a Principal Components Analysis (Wilkinson et al. 1996) of the variables of the mobility construct, resulting in three mobility components. For the construct *air quality information* I decided to focus on only one variable (*luseoft2*) indicating how often people used the app and which best represented the underlying concept. Next bivariate relationships between groups of the mobility variables, the use of the app and further control variables were analysed. The comparison of pairs of variables had the goal of determining correlations and assessing their direction as well as consistency (Wetcher-Hendricks, 2011). Finally regressions for each of the mobility components were carried out. Adding groups of variables hierarchically allowed to assess changes in correlations of

[8] See Appendix 1 for all survey questions and corresponding answer codes.

the main and control variables and to determine the variance explained by the new variables entered (Cramer, 2003).

4.1 Air quality information and mobility changes

Of the 70 individuals participating in the survey, 47 were male (67.14%) and 23 were female (32.86%). The age of the participants ranged in a normally shaped distribution from 18 to 67, with a mean of 41.11 years. Looking at the two variables which measured how often the London Air app was consulted during a month and how often air quality was checked during the day revealed that differences among users' perceptions of air quality information were high: 42.86% of the participants of the survey used the app only on a monthly basis or even less frequently, whereas 31.43% were weekly and 25.71% daily users. Based on its negative skewness, the variable was transformed with a cubic power transformation before being used as a main independent variable (*luseoft2*) for further calculations. The variable measuring daily use was not considered any further since only 7 users indicated having consulted the app more than twice daily.

Turning towards the dependent construct *mobility changes*, table A in appendix 2 provides an overview of both, the attitude variables measuring the participant's agreement or disagreement with 5 statements, and the frequency variables collecting data on effective mobility changes regarding the same subjects. More than half of the respondents disagree or strongly disagree with the statement that increased air pollution prevents them from going outside (64.29%) or affects their choice of travel route (52.86%), the time they travel or engage in outdoor activities (50.00%) or, finally, the means of travel they choose (55.71%). The answer to the question whether increased air pollution affects how users plan and organise outdoor activities in advance was answered in a more differentiated pattern, with 47.14% of participants disagreeing or strongly disagreeing, 17.14% of participants being undecided and 35.71% who agreed or strongly agreed with the statement. In comparison with the attitude variables, answers to the frequency questions resulted in lower means throughout. For each frequency question, at least 57% of respondents indicated never having made adjustments to their mobility. Weekly or daily mobility changes were only made by a minority of 5 to 10 participants per question. Taken together, the 10 mobility variables achieved a Cronbach's alpha of 0.89, indicating a high internal reliability for a multiple-item index (Knoke et al. 2002). Based on this result, a Principal Components Analysis (PCA) was conducted in order to prove the underlying concept of mobility changes (Hamilton, 2009). Consequently, the large number of variables could have been reduced to three components with a minimum eigenvalue of 1 following Kaiser's rule (Wilkinson et al. 1996). With the help of an orthogonal rotation for uncorrelated components (Hamilton, 2009) the data was transformed to maximise the variance of the squared loadings of the components on all the variables in a component matrix. The results showed that all mobility variables—except one which measured attitudes towards changing time of travel—were identified as part of the three components and together explained 74% of the overall variance in the data.

Variable	*mobilcomp1*	*mobilcomp2*	*mobilcomp3*	Unexplained
notgoout2	0.4202			.2685
frenotout2	0.5436			.2168
orgout2	0.4753			.2373
freorgout2	0.4847			.2605
routechoice2		0.3782		.3422
freroute2		0.6513		.106
travtime2				.4317
fretravtime2		0.5262		.2469
meanschoice2			0.6841	.1198
fremeanchoice2			0.5806	.2769

(loadings <.3 are absorbed)

TABLE 1: ROTATED COMPONENTS

As visualised in table 1 above, attitude and frequency variables regarding the same mobility aspect always loaded together on one component, which supports the construct validity of the measurement (Cronbach and Meehl, 1955). The first component included attitude and frequency variables regarding the decision to refuse to go outside as well as the organisation and planning of outdoor activities. The second component reflected the frequency variables on the choice of travel time and travel route as well as attitudes towards changing travel routes. The third component included attitude and frequency variables on changing the means of travel based on increased air pollution. Scores of all three components were then saved for use in further analysis.

4.2 Control variables

Looking at the control variables, the survey found that 45.71% of participants additionally used other sources than the app to access information on air quality. Further, respondents on average used 2.8 different modes of travelling when moving through London: most frequently these were walking (72.86%), taking the tube (62.86%) and driving by bus (55.71%). Distinctive groups regarding the use of public transport or travel on foot and by bike could not be identified. Instead the collected data showed that 55.71% of the sample spend more than 2 hours per day outside. Also, a high proportion of surveyed users (62.86%) perform physical outdoor activities, 12 of whom even more than 4 hours per week. Health-related questions showed that 44.29% had either heart or respiratory problems and 45.71% experienced symptoms they referred to as caused by bad air quality at least once a month. Reflecting these findings, awareness of adverse health effects due to air pollution was relatively high with a mean of 7.3 on a scale from 1 to 10. Nevertheless only three people of the whole sample protected themselves from air pollution with a respiratory filter. Upon questioning in which situation users of the app would pay more attention to air quality, the most frequently mentioned reason was increased air pollution levels (indicated by 54.29% of participants), whereas illness (32.86%), travelling by bike or on foot (32.86%), having enough time for mobility changes (30.00), doing sports outside (25.71%) and being accompanied by someone elderly or children (18.57%) produced much lower hits.

4.3 Bivariate relationships

In order to evaluate the association of the mobility variables with the independent variable measuring the extent of app usage as well as other control variables in percentage tables, I recoded the mobility components established in the Principal Components Analysis for the bivariate analysis in categorical variables. The cross-tabulations of the amount of app use with each of the three recoded mobility components showed that more changes in mobility were correlating with higher app use (for complete results see appendix 2, table B). As stated in table 2 below, the calculated chi-square for *mobilcomp1* was by trend significant (p = 0.073) and achieved higher significance for *mobilcomp2* (p = 0.025) and *mobilcomp3* (p = 0.006), indicating that the variables were effectively associated.

Variable	***mobilcomp1***	***mobilcomp2***	***mobilcomp3***
use of the app	p = 0.073**	p = 0.025*	p = 0.006*
age	p = 0.085**	p = 0.206	p = 0.064**
gender	p = 0.678	p = 0.439	p = 0.533
awareness	p = 0.307	p = 0.196	p = 0.053**
frequency of symptoms	p = 0.028*	p = 0.063**	p = 0.118
health problems	p = 0.024*	p = 0.572	p = 0.095
use of other information sources	p = 0.281	p = 0.081**	p = 0.063**
means of transport	p = 0.618	p = 0.472	p = 0.551
time spent outside	p = 0.316	p = 0.710	p = 0.628
time engaged in physical activities outside	p = 0.342	p = 0.121	p = 0.322

**significant **by trend significant*

Table 2: Bivariate Relationships

Equivalent to these results, gamma had the highest value (57.28%) for tabulation of the third mobility component with app use and lower values for the tabulation with *mobilcomp1* (32.66%) and *mobilcomp2* (49.03%). Several further cross-tabulations between the variables were performed in order to find associations within the collected data. Percentage tables including the recoded mobility components as dependent variables revealed the following relations:

Awareness of air pollution was by trend significant (p = 0.053) for the third mobility component. In contrast, the frequency of experienced symptoms was only significant (p = 0.028) for *mobilcomp1*, but only by trend for *mobilcomp2* (p = 0.063) and not significant at all for *mobilcomp3* (p = 0.118). Having either heart of respiratory problems was significantly associated with *mobilcomp1* (p = 0.024) but not with the other mobility components. Whether people used additional information sources for the app was by trend significant with *mobilcomp2* (p = 0.081) and *mobilcomp3* (p = 0.063). No associations were found between all three mobility components and the number of different means of transportation used by the participant, the time spent outside and the hours of outdoor physical activities as well as the age and gender of participants.

Furthermore, the bivariate analysis showed that having heart or respiratory problems seems to correlate positively with the frequency of experienced physical symptoms based on air pollution as well as with age. And finally people with heart or respiratory problems seem more likely to use other information sources in addition to the app.

4.4 Hierarchical multiple regression

Based on the bivariate relations found, the following variables were selected to be controlled in the regression: awareness of air pollution, frequency of experienced symptoms, existence of health problems, use of other information sources, and age.

Although no bivariate correlations with the mobility variables were found, gender was also considered as a standard demographic variable. The goal of controlling statistically for the influence of these variables was to describe the true relation between the perception of air quality information and mobility changes by eliminating alternative explanations (Knoke et al. 2002). For this purpose a hierarchical multiple regression was chosen as this procedure allows for adding groups of variables in different stages to the regression analysis and for assessing the proportion of the variance they explain at each stage (Cramer, 2003). The order of the variables can be determined by theory and moderating effects controlled for. Calculations were conducted for each of the mobility components determined in the Principal Components Analysis. The first group of independent variables entered included the age and gender variables as both were expected to have the smallest effect on mobility changes. The next group included the use of other information sources and the awareness of air pollution. Third, the two health-related variables, whether a person has respiratory or heart problems and how often symptoms are experienced, were entered. Finally the variable which had measured the use of the app was included. Dummy variables were used for the three dichotomous measurements of gender, health problems and the use of additional information sources (Agresti and Finlay, 2009), while all other variables were treated as continuous (Knoke et al. 2002). Finally the beta option was used to obtain standardised regression coefficients and to increase comparability of variables (Hamilton, 2009).

The following table shows the results for each of the mobility components (see appendix 2, tables C1-C3 for the complete results). In the first multiple regression already the first hierarchical step lead to a significant model ($F_{2,67} = 4.57$, $p = 0.014$), determined by age being a significant coefficient loading positively on the dependent variable. The greatest variance in *mobilcomp1* was explained with the variables in step 3, leading to an increase of 18.7% ($F_{6,63} = 6.72$, $p < 0.001$) in the coefficient of multiple determination (adjusted R^2)

to the highest proportional reduction in error (Agresti and Finlay, 2009). By comparison, step 4 only had a small effect, supported by the fact that the partial regression coefficient of the main predictor *luseoft2* was statistically insignificant ($t(62) = 1.42$, $p = 0.161$).

mobilcomp1					
Steps	**Added variables**	**Adj R^2**	**R^2 change**	***F* (df)**	***p***
1	gender, age	0.094		4.57 (2, 67)	0.014
2	other information sources, awareness	0.145	0.051	3.93 (4, 65)	0.006
3	health problems, frequency of symptoms	0.332	0.187	6.72 (6, 63)	0.000
4	use of the app	0.343	0.011	6.14 (7, 62)	0.000

mobilcomp2					
Steps	**Added variables**	**Adj R^2**	**R^2 change**	***F* (df)**	***p***
1	gender, age	-0.003		0.91 (2, 67)	0.409
2	other information sources, awareness	0.106	0.109	3.05 (4, 65)	0.023
3	health problems, frequency of symptoms	0.215	0.109	4.15 (6, 63)	0.001
4	use of the app	0.259	0.044	4.45 (7, 62)	0.001

mobilcomp3					
Steps	**Added variables**	**Adj R^2**	**R^2 change**	***F* (df)**	***p***
1	gender, age	-0.008		0.74 (2, 67)	0.479
2	other information sources, awareness	0.257	0.265	6.97 (4, 65)	0.000
3	health problems, frequency of symptoms	0.327	0.070	6.58 (6, 63)	0.000
4	use of the app	0.359	0.032	6.52 (7, 62)	0.000

TABLE 3: HIERARCHICAL REGRESSIONS

A similar pattern could be observed in the second hierarchical regression, where the second and the third group of variables could explain higher measures of variance in *mobilcomp2* than the main predictor *luseoft2*. Although use of the app was significant ($t(62) = 2.18$, $p = 0.033$) and positively correlated with *mobilcomp2* by leading to a change of 0.24 standard deviation (SD) in the dependent variable when it increased itself by 1 SD, the overall explained variance (25.9%) was lower than in the first hierarchical regression.

Being again significant ($t(62) = 2.05$, $p = 0.045$) in the third regression and positively correlated with *mobilcomp3*, impact of the app use was similarly small as with the prior regression, thereby explaining an additional 3.2% variance of the dependent variable. The second group of variables had the largest impact in this model, where the variable measuring use of additional information sources had the highest Beta coefficient. The overall adjusted R^2 of 35.9% indicates the best fit of the model regression line with the collected data compared to the first two models. By further comparing the three last models of the hierarchical regressions which include all the groups of variables, the following findings can be observed: of the demographic variables the partial regression coefficient of age was only significant ($t(62) = 2.40$, $p = 0.019$) in relation with *mobilcomp1* when its influence was weak but positive, whereas gender was never significant. In the second group of variables awareness was only significantly related to mobilcomp3 ($t(62) = 2.82$, $p = 0.007$), whereas people who used information sources in addition to the app always correlated positively and significantly with the dependent mobility component. In the third group of variables the presence of health problems was only significant ($t(62) = -2.20$, $p = 0.031$) in relation to *mobilcomp2,* whereas the frequency of experienced symptoms achieved significant results in all three models.

Finally the variables were checked for multicollinearity by using the Variance Inflation Factor (VIF) and condition indices which did not indicate critical results, confirming that the coefficients in the regressions above were true (Wilkinson et al. 1996). Regression diagnostics further showed that dependent and independent variables were correlating linearly. In contrast, plotting the studentised residuals against the predicted values in order to check for outliers revealed that in each of the three regressions residuals were not homoscedastic and that the models underpredict a couple of cases. Outliers had residuals from two to four standard deviations and their influence was partially very large as indicated by Cook's D (Wilkinson et al. 1996). Although it is suggested to delete these points (Cook and Weisberg, 1982), I decided to keep these cases due to the small sample in my dataset. For all the results presented it has to be considered that the sample size of 70 cases statistically underpowers the given study, as the power achieved for the first mobility component was 0.4, for the second 0.09 and for the third 0.4, based on an alpha level of 0.05. This might be the reason for finding only small effects in the assumed relations (Bryman and Cramer, 1994).

5. Discussion

The data collected and analysed will serve in this section to answer the research questions. Conclusions will be drawn by appraising the subject's theoretical context summarised in chapter two, and reflections on the relation of air quality information and mobility changes will lead to new assumptions and possible explanations of the results.

Variable	***mobilcomp1***	***mobilcomp2***	***mobilcomp3***
gender			
age	p = 0.019, ß 0.24		
use of other information sources	p = 0.021, ß 0.23	p = 0.028, ß 0.24	p = 0.000, ß 0.38
awareness			p = 0.007, ß 0.28
health problems		p = 0.031, ß -0.24	
frequency of symptoms	p = 0.001, ß 0.39	p = 0.012, ß 0.31	p = 0.050, ß 0.22
use of the app		p = 0.033, ß 0.23	p = 0.045, ß 0.20
Model overall	$F_{7,62} = 6.14$, $p < 0.001$	$F_{7,62} = 4.45$, $p < 0.001$	$F_{7,62} = 6.52$, $p < 0.001$
Adj. R^2	34.27%	25.94%	35.92%

(blanks for p > 0.05)

Table 4: Summary of the results

5.1 First research question

Answering the first research question, especially responses to the frequency and attitude questions regarding mobility changes shall be considered (see appendix 2, table A). Although the number of people who agree or strongly agree with air pollution leading them to changes is moderate (from 21% to 35% per question), the answers to the frequency questions show that weekly and daily changes only occur in a minority (from 7% to 14% per question). Despite these small rates the bivariate associations are determined by the amount of app use significant for the second and third mobility component, which concerns the change of travel route, the change of travel time and the choice of means of transport. Further evidence of this relation is given in the hierarchical regressions, where it is shown that the use of the app explains a 4.4% variance in the dependent variable *mobilcomp2* and 3.2% variance in the dependent variable *mobilcomp3*. Therefore the first research question can be answered positively by stating that users indeed perceive changes in their everyday mobility as being based on air quality information provided by the app and that the implications of this information are reflected in their choice of travel route, travel time and means of transport.

5.2 Second research question

The second research question follows the assumption that the reaction to air quality information might be affected by additional variables. As the bivariate relationships have shown, control variables beside the main predictor do have implications on mobility changes, although they are significant for *mobilcomp2* and *mobilcomp3* only by trend. The second mobility component containing changes in travel route and travel time is therefore not only significantly correlated to the use of the app, but also associated with the use of additional information sources and the experience of negative health symptoms. The third mobility component, reflecting changes in the choice of means of travel, is by trend significant with age, awareness of air pollution and again regarding the use of additional information sources. As with the changes in travel time and travel route, the choice of means of transport significantly correlates with the use of the app. Finally, the first mobility component referring to the organisation of outdoor activities and the decision on going outside, shows significant correlations to the experience of health symptoms and the health condition of the users, and the use of the app and age are by trend significant with these mobility changes.

These results have been partially reflected in the regression. The relevance of the app use has remained significant for the change of travel route, travel time and means of transport, just as the frequency of symptoms remained significant for the decision on going outside and the organisation of outdoor activities. The gender variable remains insignificant for all mobility components. The other relations which have been by trend significant either disappeared or became fully significant in the regression when all variables were considered. As a consequence the results indicate that the organisation of outdoor activities and decisions on going outside are mainly driven by the frequency of experienced health symptoms and correlate with higher age and the use of additional information sources. The consideration of all explanatory variables therefore sorted out the use of the app and health problems of the participants. Instead age and the use of additional information became significant. Changes in travel time and travel route are also mainly affected by the frequency of experienced symptoms, whereas the use of the app, the consideration of additional information sources and negatively correlating health problems have moderate influences. Running the regression therefore revealed increased impacts of the frequency of experienced symptoms, participants' health conditions and the use of additional information sources. The change in the means of travel—which is the object of the third mobility component—seems to be mainly determined by the fact whether people use additional information sources. The amount of app use, the awareness and the frequency of symptoms have moderate implications on the choice of means of travel. In comparison to the bivariate relations, considering all control variables revealed lower influences of age but higher impact of the air pollution awareness, the frequency of experienced symptoms and the use of additional information sources. The second research question can therefore be answered by stating that the impacts of air quality information on mobility changes vary by awareness, frequency of symptoms, health problems as well as the use of additional information sources. Furthermore, the influence of air quality information for some mobility changes, particularly the organisation of outdoor activities and the decision on going outside, is not relevant and replaced through other explanatory variables, which are age, frequency of symptoms and the use of other information sources. Although the use of air quality information provided by the app is still a significant and influencing factor for the second and third mobility component, changes in mobility are generally better explained by other variables with stronger beta coefficients. Especially the use of additional information sources, the frequency of experienced symptoms and the awareness of air pollution might be better predictors of mobility changes than air quality information.

5.3 Interpretation of the results

Starting from the general perspective of admitting air pollution as a cause of adverse health effects, the variation in its implications has to be considered when interpreting the results. Comprising users in the sample who differ regarding health condition, amount of exposure to air pollution or age means collecting results of a very diverse group of people who may differ strongly regarding their susceptibility to negative health effects of air pollution (Delfino et al. 1998; Kelly et al. 2012). Additionally, users of the London air app might perceive the relevance of air quality information to themselves based on health problems they are aware of as well as symptoms they experience and assume to be due to air pollution (COMEAP, 2011). In general, people seem to overestimate their likelihood to perform mobility changes. As is visible in the answers to the attitude and frequency questions, a fair number of users of the London Air app agree/strongly agree that air quality information influences their mobility. However, only for a modest part of the sample effective changes could be measured, and the explained variance based on air quality information is small. My findings further reveal that heart or respiratory problems of susceptible groups have only a minor impact on changes in travel time and travel routes. However, the frequency of experienced health symptoms perceived by the users as based on air pollution has major implications on several aspects of their mobility behaviour. Especially regarding the organisation of outdoor activities and decisions to go out, but also regarding changes in travel time, travel route and travel choice, its influence is high and by far stronger than the amount of app use. This finding confirms results of Semenza et al. (2008) who state that subjective perception of air quality has higher impacts on behavioural changes than air quality advisories. As with health condition, age only has a minor influence on mobility changes. Older people alter their organisation of outdoor activities and decisions on going outside more often due to air pollution than younger people. Together with the frequency of experienced symptoms and the use of other information sources, the significance of age to this mobility component makes sense as older people might not only experience more symptoms but also be less confident with the use of the app and hence rely more on other media. Gender, which was the other demographic variable considered in the regression, was not correlated to any mobility components. This result was surprising insofar as prior findings of Ren and Kwan (2009) suggested that gender would play a major role when it comes to the impacts of the Internet on people's activity and travel patterns. Gender might therefore have less of an impact when related to the mobile Internet or health and mobility behaviours.

After health conditions and age of participants, awareness of air pollution was another variable only significant for one mobility component. Its impact was comparably high, as it influenced the choice of the means of travel stronger than the consultancy of the app and the frequency of experienced symptoms. Although the choice of means of transport was the only mobility aspect correlated with awareness, its high mean among app users reflects prior reports on the generally high awareness of air pollution among the public (COMEAP, 2011). This finding could reflect increased responsiveness to and consciousness of air pollution determined by the app (Boulos, 2004; Hipólito, 2007), or it could be the original reason for acquiring access to the service.

Assessment of the application's overall value for information on air pollution shows that almost half the users also consider additional media for air quality information. The distinguishing feature of the mobile Internet, being capable of providing spatio-temporally changing information and taking advantage of the disconnected space-time relationship of mobile phones (Alexander at al. 2011; Huomo, 2001), does not make it an exclusive medium for the dissemination of air quality data. Functioning instead as a complement to other media, this might be the reason why the correlation of the app's use with mobility changes is small regarding decisions on changing travel time, travel routes and means of transport.

The app has no significant relevance at all for users deciding whether to go outside or planning outdoor activities. This can be explained by the fact that these decisions are mainly made at home where other information sources can be accessed easily. The significance of the anywhere and anytime accessibility of the mobile Internet to our mobility as reflected in its provision of an increased flexibility as suggested by Kwan (2006) as well as by Graham and Marvin (1996) must therefore be specifically related to time spent outdoors. Understanding that the mobile Internet is a better basis for decision-making processes when other media are not available and becomes crucial when we are outside of our home and moving through urban space might conflict momentarily with the limited extent of mobility changes demonstrated by my study. Even if the likelihood to engage in mobility changes based on the mobile Internet appears unchanged or even to have decreased by comparison with Semenza's et al. (2008) results which show behavioural changes executed by 10–15% of participants based on air pollution information through TV, Radio and Newspaper, Aguiléra et al.'s argument that 'nothing revolutionary has occurred' (2012, p.666) in the relationship of ICTs and travel still has to be questioned. Beside the fact that people tend to use information inefficiently when making decisions (Clark, 2010) or that they might not be able to modify their behaviour because of a lack of flexibility (Aguiléra et al. 2012), I would argue that not performing changes in mobility might also be the result of being better informed. This means that having the right information at the right time and place might also lead users to decide not to change their mobility, because they may realise that in their time and place there is no need to do so. In this case the mobile Internet would still alter our perception of space and produce spatiality by calculating our mobilities (De Souza e Silva, 2006; Wilson, 2012) even if effective mobility changes were small. The prime question to ask therefore is whether the information provided through the mobile Internet is effectively integrated in the decision-making process of health and travel behaviour (Ajzen, 1985) before analysing changes in mobility, which are a possible consequence as likely as are no changes in mobility. This perspective on the subject can also explain the gap between the frequency of effective changes and the attitude app users have towards altering their mobility based on air quality. It further draws attention to the fact that mobility—whether changed or not—is not necessarily a causally related consequence of air quality information. Mobility changes may also be due, as my findings suggest, to subjective perceptions of negative air quality impacts as reflected in the experience of adverse symptoms. Whether air quality information on the mobile Internet has broader implications, as for instance on the awareness of air pollution, public health or the perception of space therefore cannot be determined with the collected data.

In summary and with regard to domestication theory (Green and Haddon, 2009), this thesis suggests that the mobile Internet changes our everyday activities by complementing the use of other media in general, while offering an additional benefit when we are moving through space due to its ability to provide spatio-temporally changing information almost in real-time. The mobile Internet does, however, not lead automatically to more changes in our mobility, instead it provides an elaborate basis for making better decisions regarding our movement. However, if we decide to make changes, than these are mostly motivated by perceived health symptoms and modify our travel time, travel routes and the means of transport we use.

There are still some possibilities concerning how we can improve the provision of air quality information as a basis for decision-making processes and therefore increase efficient decisions on our mobility when they are actually needed. As Fjeldsoe et al. (2009) point out, customisation can lead to an increase of behavioural changes. A similar argument has been put forward by Halko and Kientz (2010) and includes the accommodation of the needs of diverse users. Responsiveness and interactivity, which can both improve the outcomes of behaviour change interventions (Atkinson and Gold 2002), could be achieved through taking the users' GPS positions into account, therefore incorporating their location into the decision-making process. Also, neogeography (Graham 2010) and real-time urban monitoring with mobile phones (Calabrese et al. 2010) could increase engagement and contribute to establishing an Internet of places (Ratti et al. 2011), live urbanism (Resch et al. 2012) and mesh networks (Solow-Niederman et al. 2012).

6. Conclusion

Following the goal of exploring the implications of the mobile Internet on our everyday lives as proposed by domestication theory (Green and Haddon, 2009), this study contributed in several ways to the subject. First, the explorative analytical approach determined three mobility components which constituted the dependent variables of the thesis. Second, the research questions were answered by finding that air quality information provided by the London Air application can alter mobility regarding travel route, travel time and the means of transport chosen by participants of the study. Additionally, this thesis suggests that also age, awareness of air pollution, the frequency of symptoms and the use of additional information sources are significant predictors of mobility changes. These results confirm some of the findings in related fields, but also expand on previous studies first and foremost by combining the dissemination of air quality information with the mobile Internet and mobility in urban environments and by examining their interactions with the help of domestication studies. Bringing these themes together, the current study concludes that the mobile Internet is complementary to other media as a supply of spatio-temporally changing information, but gains significant influence on decisions related to our health and mobility when we are outside of our home. Furthermore, this thesis opens a new perspective on the subject by understanding that mobility changes are a possible but not necessary product of successful air quality implications. Instead the utilisation of the app may also lead to no changes in mobility when a person has already fully changed to low air pollution travel patterns or realises that there is no change required. In this case the information provided by the mobile Internet is nevertheless a significant part of the decision-making process concerning content of health and mobility behaviour. Overall a key strength of the research at hand is its focused data collection from people who use or at least meet all the preconditions for using health information provided by the mobile Internet.

Limitations to these findings have to be considered based on the methods employed, as for instance the decision to choose a cross-sectional design that does not allow determining causal relationships or the non-random selection of the sample. Furthermore, the collected data have shortcomings both in terms of accuracy and sample size. Regarding the primer, the collection of GPS data on app users could have offered more precise results on mobility behaviour, and, relating to the latter, further initiatives against non-response could have increased the number of participants. Beside these, the study did not consider biases by air pollution variations during the data collection and pollution concentrations might have influenced the responses. Finally, this research did take other reactions than mobility changes to air quality information into account. A higher intake of medication as result of higher air pollution (COMEAP, 2011) might have replaced mobility changes.

Additional research should address the limitations of this study and expand the examination of the mobile Internet by incorporating location-based services. Augmented environmental information (Hipólito, 2007) by taking users' positions into account plays a major role in urban mobility and could go one step further in supporting citizens in their decision-making processes on health behaviours.

Appendix

Appendix 1: Codebook

Question	Answer options		Code	Variable-name	Question-/ Variable-type
I have read this form and agree to take part in the study.	Yes No		1 0	agree2	Dichotomous
Independent construct: *Air Quality Information*					
How often do you use the London Air App when you are in London?	Daily Weekly Monthly Less than monthly		4 3 2 1	useoft2 (transformed with cubic power transformation to luseoft2)	Ordinal
On an average day using the London Air App, how often do you check the air pollution, either by reading the notifications or directly in the app?	1-2 times 3-4 times 5-6 times 7+ times		1 2 3 4	useday2	Ordinal
What other information sources than the London Air app do you use to learn about air pollution?	No other	Yes No	1 0	othernone2 (recoded to yesotherinf)	Multiple-choice question, dichotomous
	Radio	Yes No	1 0	otherradio2	
	Newspaper	Yes No	1 0	otherpaper2	
	Television	Yes No	1 0	othervision2	
	Internet	Yes No	1 0	otherinternet2	
	Other apps	Yes	1	otherapp2	

		No	0		
Dependent construct: *Mobility*					
Please indicate how you feel about the following statement: "Increased air pollution levels prevent me from going outside".	Strongly disagree Disagree Undecided Agree Strongly agree		1 2 3 4 5	notgoout2 (part of bicomphigh1 and mobilcomp1)	Likert-scale, ordinal
On average, how frequently do you decide not to go outside because of increased air pollution?	never less than monthly at least once a month at least once a week one and more times a day		1 2 3 4 5	frenotout2 (part of bicomphigh1 and mobilcomp1)	Ordinal
Please indicate how you feel about the following statement: "Increased air pollution levels affect how I plan and organise outdoor activities in advance".	Strongly disagree Disagree Undecided Agree Strongly agree		1 2 3 4 5	orgout2 (part of bicomphigh1 and mobilcomp1)	Likert-scale, ordinal
On average, how frequently do you adjust or change your plans for outdoor activities because of increased air pollution?	never less than monthly at least once a month at least once a week one and more times a day		1 2 3 4 5	freorgout2 (part of bicomphigh1 and mobilcomp1)	Ordinal
Please indicate how you feel about the following statement: "Increased air pollution levels along the fastest route affect my choice of travel route".	Strongly disagree Disagree Undecided Agree Strongly agree		1 2 3 4 5	routechoice2 (part of bicomphigh2 and mobilcomp2)	Likert-scale, ordinal
On average, how frequently do you change your travel route or route for other outdoor activities because of increased air pollution?	never less than monthly at least once a month at least once a week		1 2 3 4	freroute2 (part of bicomphigh2 and mobilcomp2)	Ordinal

	one and more times a day		5		
Please indicate how you feel about the following statement: "Increased air pollution levels affect the time I chose to travel or do outdoor activities".	Strongly disagree Disagree Undecided Agree Strongly agree		1 2 3 4 5	travtime2 (neglected after PCA)	Likert-scale, ordinal
On average, how frequently do you reschedule travelling or other outdoor activities because of increased air pollution?	never less than monthly at least once a month at least once a week one and more times a day		1 2 3 4 5	fretravtime2 (part of bicomphigh2 and mobilcomp2)	Ordinal
Please indicate how you feel about the following statement: "Increased air pollution levels affect the means of travel I choose".	Strongly disagree Disagree Undecided Agree Strongly agree		1 2 3 4 5	meanschoice2 (part of bicomphigh3 and mobilcomp3)	Likert-scale, ordinal
On average, how frequently do you change your means of travel because of increased air pollution?	never less than monthly at least once a month at least once a week one and more times a day		1 2 3 4 5	fremeanschoice2 (part of bicomphigh3 and mobilcomp3)	Ordinal
Control Variables					
How do you usually travel around London? Please select those means of travel which you use on regular basis.	tube	Yes No	1 0	traveltube	Multiple-choice question, dichotomous
	train	Yes No	1 0	traveltrain	
	car	Yes No	1 0	travelcar	
	bike	Yes No	1 0	travelbike	
	foot	Yes	1	travelfoot	

		No	0		
	bus	Yes No	1 0	travelbus	
On a regular day in London, how many hours do you spend outdoors on average?	0-2 hours 3-4 hours 5-6 hours 7-8 hours 9-10 hours 10+ hours		1 2 3 4 5 6	timeoutnorm	Ordinal
During a typical week in London, how many hours do you usually spend doing sports and other strenuous physical activities outdoors?	0 hours 1-4 hours 5-8 hours 9-12 hours 13-16 hours 17+ hours		0 1 2 3 4 5	timeoutphys	Ordinal
Do you protect yourself with a respiratory filter or in another way when you are travelling outside?	No Yes		0 1	protect2	Dichotomous
Do you have heart problems?	No Yes		0 1	heartprob (part of healthprob)	Dichotomous
Do you have respiratory problems?	No Yes		0 1	respprob (part of healthprob)	Dichotomous
How frequently do you experience physical symptoms that you think may be caused by air pollution?	never less than monthly at least once a month at least once a week one and more times a day		1 2 3 4 5	fresymptoms2	Ordinal
On a scale of 1 to 10, where 10 is a strong effect and 1 only a weak effect, how much do you think air pollution can affect your health?	1 – 10		1 2 3 4 5	awareness	Ordinal

			6 7 8 9 10		
Do you pay more attention to air pollution before going outside or when you are already travelling in any of the following situations? Please tick all that apply.	when I'm accompanied by elderly people or children	Yes No	1 0	attelderly	Multiple-choice question without minimum responses, dichotomous
	when I'm doing sports or other strenuous physical activities outside	Yes No	1 0	attsports	
	when I have enough time to take routes with lower pollution levels	Yes No	1 0	atttime	
	when I'm travelling by bike or foot	Yes No	1 0	attbike	
	when I'm ill or when I feel unwell	Yes No	1 0	attill	
	when air pollution levels are high	Yes No	1 0	atthigh	
You are	Male Female		0 1	gender (recoded to female)	Dichotomous
Year you were born	1910-1994 // 18-102 years		1	birthyear (recoded to age)	Interval

Appendix 2: Statistical Analysis

Table A: Attitude and Frequency Variables for Changes in Mobility

Attitude-Variable	Strongly disagree	Disagree	Un-decided	Agree	Strongly agree	Total
Notgoout2: Increased air pollution levels prevent me from going outside	11 15.71	34 48.57%	10 14.29%	11 15.71%	4 5.71%	70 100%
Orgout2: Increased air pollution levels affect how I plan and organise outdoor activities in advance.	12 17.14%	21 30.00%	12 17.14%	21 30.00%	4 5.71%	70 100%
Routechoice2: Increased air pollution levels along the fastest route affect my choice of travel route.	12 17.14%	25 35.17%	12 17.14%	13 18.57%	8 11.43%	70 100%
Travtime2: Increased air pollution levels affect the time I chose to travel or do outdoor activities.	9 12.86%	26 37.14%	15 21.43%	13 18.57%	7 10.00%	70 100%
Meanschoice2: Increased air pollution levels affect the means of travel I choose.	14 20.00%	25 35.71%	8 11.43%	18 25.71%	5 7.14%	70 100%

Frequency-Variables	Never	Less than monthly	At least once a month	At least once a week	One and more times a day	Total
Frenotout2: On average, how frequently do you decide not to go outside because of increased air pollution?	46 65.71%	14 20.00%	5 7.14%	3 4.29%	2 2.86%	70 100%
Freorgout2: On average, how frequently do you adjust or	41 58.57%	17 24.29%	6 8.57%	4 5.71%	2 2.86%	70 100%

change your plans for outdoor activities because of increased air pollution?						
Freroute2: On average, how frequently do you change your travel route or route for other outdoor activities because of increased air pollution?	40 57.14%	13 18.57%	7 10.00%	5 7.14%	5 7.14%	70 100%
Fretravtime2: On average, how frequently do you reschedule travelling or other outdoor activities because of increased air pollution?	41 58.57%	19 27.14%	4 5.71%	1 1.43%	5 7.14%	70 100%
Fremeanschoice2: On average, how frequently do you change your means of travel because of increased air pollution?	43 61.43%	15 21.43%	5 7.14%	4 5.71%	3 4.29%	70 100%

TABLE B: CROSSTABULATION OF LUSEOFT2 WITH BIMOBILCOMP1/2/3

```
-> tabulation of luseoft2 by bicomphigh1

+----------------+
| Key            |
|----------------|
|   frequency    |
| row percentage |
+----------------+

           |      bicomphigh1
  luseoft2 |         0          1 |     Total
-----------+----------------------+----------
         1 |        16          5 |        21
           |     76.19      23.81 |    100.00
-----------+----------------------+----------
         8 |         7          2 |         9
           |     77.78      22.22 |    100.00
-----------+----------------------+----------
        27 |         9         13 |        22
           |     40.91      59.09 |    100.00
-----------+----------------------+----------
        64 |        10          8 |        18
           |     55.56      44.44 |    100.00
-----------+----------------------+----------
     Total |        42         28 |        70
           |     60.00      40.00 |    100.00

          Pearson chi2(3) =   6.9679   Pr = 0.073
                    gamma =   0.3266  ASE = 0.166


-> tabulation of luseoft2 by bicomphigh2

+----------------+
| Key            |
|----------------|
|   frequency    |
| row percentage |
+----------------+

           |      bicomphigh2
  luseoft2 |         0          1 |     Total
-----------+----------------------+----------
         1 |        14          7 |        21
           |     66.67      33.33 |    100.00
-----------+----------------------+----------
         8 |         6          3 |         9
           |     66.67      33.33 |    100.00
-----------+----------------------+----------
        27 |         7         15 |        22
           |     31.82      68.18 |    100.00
-----------+----------------------+----------
        64 |         5         13 |        18
           |     27.78      72.22 |    100.00
-----------+----------------------+----------
     Total |        32         38 |        70
           |     45.71      54.29 |    100.00

          Pearson chi2(3) =   9.3524   Pr = 0.025
                    gamma =   0.4903  ASE = 0.148
```

```
-> tabulation of luseoft2 by bicomphigh3

+-----------------+
| Key             |
|-----------------|
|    frequency    |
| row percentage  |
+-----------------+

           |      bicomphigh3
  luseoft2 |         0          1 |     Total
-----------+----------------------+----------
         1 |        13          8 |        21
           |     61.90      38.10 |    100.00
-----------+----------------------+----------
         8 |         6          3 |         9
           |     66.67      33.33 |    100.00
-----------+----------------------+----------
        27 |         6         16 |        22
           |     27.27      72.73 |    100.00
-----------+----------------------+----------
        64 |         3         15 |        18
           |     16.67      83.33 |    100.00
-----------+----------------------+----------
     Total |        28         42 |        70
           |     40.00      60.00 |    100.00

          Pearson chi2(3) =  12.4333   Pr = 0.006
                    gamma =   0.5728  ASE = 0.136
```

TABLE C1: RESULTS HIERARCHICAL REGRESSION MOBILCOMP1

```
hireg mobilcomp1 (female age) (yesotherinf awareness) (healthprob fresymptoms2)
(luseoft2), r(beta)

Model 1:
   Variables in Model:
   Adding           : female age
      Source |       SS       df       MS              Number of obs =      70
-------------+------------------------------           F(  2,    67) =    4.57
       Model |  24.2557766     2  12.1278883           Prob > F      =  0.0138
    Residual |  177.922312    67   2.6555569           R-squared     =  0.1200
-------------+------------------------------           Adj R-squared =  0.0937
       Total |  202.178089    69  2.93011723           Root MSE      =  1.6296

------------------------------------------------------------------------------
  mobilcomp1 |      Coef.   Std. Err.      t    P>|t|                     Beta
-------------+----------------------------------------------------------------
      female |  -.0067726    .414759    -0.02   0.987                -.0018718
         age |   .0448826   .0148522     3.02   0.004                 .3464015
       _cons |   -1.84309    .652806    -2.82   0.006                        .
------------------------------------------------------------------------------

Model 2:
   Variables in Model: female age
   Adding           : yesotherinf awareness
      Source |       SS       df       MS              Number of obs =      70
-------------+------------------------------           F(  4,    65) =    3.93
       Model |  39.3678004     4  9.84195011           Prob > F      =  0.0064
    Residual |  162.810289    65  2.50477367           R-squared     =  0.1947
-------------+------------------------------           Adj R-squared =  0.1452
       Total |  202.178089    69  2.93011723           Root MSE      =  1.5826

------------------------------------------------------------------------------
  mobilcomp1 |      Coef.   Std. Err.      t    P>|t|                     Beta
-------------+----------------------------------------------------------------
      female |  -.0338426    .404787    -0.08   0.934                -.0093532
         age |   .0410144    .014577     2.81   0.006                 .3165471
 yesotherinf |    .717243   .3816962     1.88   0.065                 .2102408
   awareness |   .1343096   .0955641     1.41   0.165                 .1593799
       _cons |  -2.983501   .8771849    -3.40   0.001                        .
------------------------------------------------------------------------------
R-Square Diff. Model 2 - Model 1 = 0.075   F(2,65) =  3.017  p = 0.056

Model 3:
   Variables in Model: female age  yesotherinf awareness
   Adding           : healthprob fresymptoms2
      Source |       SS       df       MS              Number of obs =      70
-------------+------------------------------           F(  6,    63) =    6.72
       Model |  78.9024421     6   13.150407           Prob > F      =  0.0000
    Residual |  123.275647    63   1.9567563           R-squared     =  0.3903
-------------+------------------------------           Adj R-squared =  0.3322
       Total |  202.178089    69  2.93011723           Root MSE      =  1.3988

------------------------------------------------------------------------------
  mobilcomp1 |      Coef.   Std. Err.      t    P>|t|                     Beta
-------------+----------------------------------------------------------------
      female |  -.5662852   .3775004    -1.50   0.139                -.1565064
         age |   .0313234   .0132198     2.37   0.021                 .2417525
 yesotherinf |   .8847083   .3422806     2.58   0.012                 .2593288
   awareness |   .0723941   .0874171     0.83   0.411                 .0859072
  healthprob |   .4908396    .358137     1.37   0.175                 .1434619
fresymptoms2 |   .5986746   .1560022     3.84   0.000                  .428227
       _cons |  -3.731643    .793137    -4.70   0.000                        .
------------------------------------------------------------------------------
R-Square Diff. Model 3 - Model 2 = 0.196   F(2,63) = 10.102  p = 0.000
```

```
Model 4:
   Variables in Model: female age  yesotherinf awareness  healthprob
fresymptoms2
   Adding           : luseoft2
      Source |       SS       df       MS              Number of obs =      70
-------------+------------------------------           F(  7,    62) =    6.14
       Model |  82.7768762     7  11.825268            Prob > F      =  0.0000
    Residual |  119.401213    62  1.92582601           R-squared     =  0.4094
-------------+------------------------------           Adj R-squared =  0.3427
       Total |  202.178089    69  2.93011723           Root MSE      =  1.3877

------------------------------------------------------------------------------
  mobilcomp1 |      Coef.   Std. Err.      t    P>|t|                     Beta
-------------+----------------------------------------------------------------
      female |  -.4884276   .3785064    -1.29   0.202                -.1349886
         age |   .0314813   .0131154     2.40   0.019                 .2429711
 yesotherinf |   .8119236   .3434201     2.36   0.021                 .2379939
   awareness |   .0690028   .0867564     0.80   0.429                  .081883
  healthprob |    .451036   .3564017     1.27   0.210                 .1318282
fresymptoms2 |   .5483238   .1587833     3.45   0.001                 .3922115
    luseoft2 |   .0100683   .0070984     1.42   0.161                 .1452013
       _cons |  -3.828129   .7897785    -4.85   0.000                        .
------------------------------------------------------------------------------
R-Square Diff. Model 4 - Model 3 = 0.019   F(1,62) =  2.012  p = 0.161


Model  R2      F(df)             p         R2 change  F(df) change       p
   1:  0.120   4.567(2,67)       0.014
   2:  0.195   3.929(4,65)       0.006     0.075      3.017(2,65)        0.056
   3:  0.390   6.721(6,63)       0.000     0.196     10.102(2,63)        0.000
   4:  0.409   6.140(7,62)       0.000     0.019      2.012(1,62)        0.161
```

TABLE C2: RESULTS HIERARCHICAL REGRESSION MOBILCOMP2

```
hireg mobilcomp2 (female age) (yesotherinf awareness) (healthprob fresymptoms2)
(luseoft2), r(beta)

Model 1:
   Variables in Model:
   Adding           : female age
      Source |       SS       df       MS              Number of obs =      70
-------------+------------------------------           F(  2,    67) =    0.91
       Model |  4.22055741     2  2.11027871           Prob > F      =  0.4086
    Residual |  155.867213    67  2.32637632           R-squared     =  0.0264
-------------+------------------------------           Adj R-squared = -0.0027
       Total |  160.087771    69  2.32011262           Root MSE      =  1.5252

------------------------------------------------------------------------------
  mobilcomp2 |      Coef.   Std. Err.      t    P>|t|                     Beta
-------------+----------------------------------------------------------------
      female |   .3963592   .3882022     1.02   0.311                 .1231044
         age |   .0119343   .0139012     0.86   0.394                 .1035114
       _cons |   -.620904   .6110072    -1.02   0.313                        .
------------------------------------------------------------------------------

Model 2:
   Variables in Model: female age
   Adding           : yesotherinf awareness
      Source |       SS       df       MS              Number of obs =      70
-------------+------------------------------           F(  4,    65) =    3.05
       Model |    25.29101     4  6.32275249           Prob > F      =  0.0229
    Residual |  134.796761    65  2.07379632           R-squared     =  0.1580
-------------+------------------------------           Adj R-squared =  0.1062
       Total |  160.087771    69  2.32011262           Root MSE      =  1.4401
```

```
------------------------------------------------------------------------------
  mobilcomp2 |      Coef.   Std. Err.      t    P>|t|                     Beta
-------------+----------------------------------------------------------------
      female |    .338599   .3683201     0.92   0.361                 .1051648
         age |   .0065289   .0132638     0.49   0.624                 .0566279
 yesotherinf |   .6509809   .3473095     1.87   0.065                 .2144406
   awareness |   .2085283   .0869548     2.40   0.019                 .2780864
       _cons |  -2.199533     .79816    -2.76   0.008                        .
------------------------------------------------------------------------------
R-Square Diff. Model 2 - Model 1 = 0.132   F(2,65) =  5.080  p = 0.009

Model 3:
   Variables in Model: female age  yesotherinf awareness
   Adding            : healthprob fresymptoms2
      Source |       SS       df       MS              Number of obs =      70
-------------+------------------------------           F(  6,    63) =    4.15
       Model |  45.3468731     6  7.55781219           Prob > F      =  0.0014
    Residual |  114.740898    63  1.82128409           R-squared     =  0.2833
-------------+------------------------------           Adj R-squared =  0.2150
       Total |  160.087771    69  2.32011262           Root MSE      =  1.3495

------------------------------------------------------------------------------
  mobilcomp2 |      Coef.   Std. Err.      t    P>|t|                     Beta
-------------+----------------------------------------------------------------
      female |   .0611835   .3641983     0.17   0.867                 .0190029
         age |    .007788    .012754     0.61   0.544                 .0675482
 yesotherinf |   .8354248   .3302195     2.53   0.014                 .2751985
   awareness |   .1364643   .0843368     1.62   0.111                 .1819842
  healthprob |  -.6839637   .3455172    -1.98   0.052                -.2246561
fresymptoms2 |   .4597428   .1505051     3.05   0.003                  .369561
       _cons |  -2.551721   .7651889    -3.33   0.001                        .
------------------------------------------------------------------------------
R-Square Diff. Model 3 - Model 2 = 0.125   F(2,63) =  5.506  p = 0.006

Model 4:
   Variables in Model: female age  yesotherinf awareness  healthprob
fresymptoms2
   Adding            : luseoft2
      Source |       SS       df       MS              Number of obs =      70
-------------+------------------------------           F(  7,    62) =    4.45
       Model |  53.5493777     7   7.6499111           Prob > F      =  0.0005
    Residual |  106.538393    62  1.71836118           R-squared     =  0.3345
-------------+------------------------------           Adj R-squared =  0.2594
       Total |  160.087771    69  2.32011262           Root MSE      =  1.3109

------------------------------------------------------------------------------
  mobilcomp2 |      Coef.   Std. Err.      t    P>|t|                     Beta
-------------+----------------------------------------------------------------
      female |   .1744679   .3575377     0.49   0.627                 .0541876
         age |   .0080177   .0123888     0.65   0.520                 .0695407
 yesotherinf |   .7295216   .3243952     2.25   0.028                 .2403128
   awareness |   .1315299   .0819503     1.60   0.114                 .1754039
  healthprob |  -.7418787   .3366577    -2.20   0.031                -.2436789
fresymptoms2 |   .3864813    .149987     2.58   0.012                 .3106703
    luseoft2 |   .0146496   .0067051     2.18   0.033                 .2374256
       _cons |  -2.692111   .7460261    -3.61   0.001                        .
------------------------------------------------------------------------------
R-Square Diff. Model 4 - Model 3 = 0.051   F(1,62) =  4.773  p = 0.033


Model  R2      F(df)             p         R2 change  F(df) change       p
   1:  0.026   0.907(2,67)       0.409
   2:  0.158   3.049(4,65)       0.023     0.132      5.080(2,65)        0.009
   3:  0.283   4.150(6,63)       0.001     0.125      5.506(2,63)        0.006
   4:  0.335   4.452(7,62)       0.000     0.051      4.773(1,62)        0.033
```

TABLE C3: RESULTS HIERARCHICAL REGRESSION MOBILCOMP3

```
. hireg mobilcomp3 (female age) (yesotherinf awareness) (healthprob
fresymptoms2) (luseoft2), r(beta)

Model 1:
   Variables in Model:
   Adding            : female age
      Source |       SS       df       MS              Number of obs =      70
-------------+------------------------------           F(  2,    67) =    0.74
       Model |  3.36582044     2  1.68291022           Prob > F      =  0.4788
    Residual |  151.423558    67   2.2600531           R-squared     =  0.0217
-------------+------------------------------           Adj R-squared = -0.0075
       Total |  154.789378    69  2.24332432           Root MSE      =  1.5033

------------------------------------------------------------------------------
  mobilcomp3 |      Coef.   Std. Err.      t    P>|t|                     Beta
-------------+----------------------------------------------------------------
      female |   -.181163   .3826285    -0.47   0.637                 -.057222
         age |   .0155341   .0137016     1.13   0.261                 .1370203
       _cons |  -.5791492   .6022345    -0.96   0.340                        .
------------------------------------------------------------------------------

Model 2:
   Variables in Model: female age
   Adding            : yesotherinf awareness
      Source |       SS       df       MS              Number of obs =      70
-------------+------------------------------           F(  4,    65) =    6.97
       Model |  46.4530775     4  11.6132694           Prob > F      =  0.0001
    Residual |  108.336301    65  1.66671232           R-squared     =  0.3001
-------------+------------------------------           Adj R-squared =  0.2570
       Total |  154.789378    69  2.24332432           Root MSE      =   1.291

------------------------------------------------------------------------------
  mobilcomp3 |      Coef.   Std. Err.      t    P>|t|                     Beta
-------------+----------------------------------------------------------------
      female |  -.2379837   .3301966    -0.72   0.474                -.0751693
         age |   .0086108   .0118909     0.72   0.472                 .0759524
 yesotherinf |   1.136203   .3113608     3.65   0.001                 .3806302
   awareness |   .2491419   .0779545     3.20   0.002                 .3378857
       _cons |  -2.613975   .7155454    -3.65   0.001                        .
------------------------------------------------------------------------------
R-Square Diff. Model 2 - Model 1 = 0.278   F(2,65) = 12.926  p = 0.000

Model 3:
   Variables in Model: female age  yesotherinf awareness
   Adding            : healthprob fresymptoms2
      Source |       SS       df       MS              Number of obs =      70
-------------+------------------------------           F(  6,    63) =    6.58
       Model |  59.6416987     6  9.94028312           Prob > F      =  0.0000
    Residual |  95.1476795    63  1.51028063           R-squared     =  0.3853
-------------+------------------------------           Adj R-squared =  0.3268
       Total |  154.789378    69  2.24332432           Root MSE      =  1.2289

------------------------------------------------------------------------------
  mobilcomp3 |      Coef.   Std. Err.      t    P>|t|                     Beta
-------------+----------------------------------------------------------------
      female |  -.5429466   .3316484    -1.64   0.107                -.1714946
         age |   .0028027   .0116141     0.24   0.810                 .0247214
 yesotherinf |   1.228154   .3007064     4.08   0.000                 .4114339
   awareness |   .2153036   .0767993     2.80   0.007                 .2919944
  healthprob |   .3194884   .3146369     1.02   0.314                 .1067207
fresymptoms2 |   .3368649   .1370538     2.46   0.017                 .2753819
       _cons |  -3.044018   .6968008    -4.37   0.000                        .
------------------------------------------------------------------------------
R-Square Diff. Model 3 - Model 2 = 0.085   F(2,63) =  4.366  p = 0.017
```

```
Model 4:
   Variables in Model: female age  yesotherinf awareness  healthprob
fresymptoms2
   Adding           : luseoft2
      Source |       SS       df       MS              Number of obs =      70
-------------+------------------------------           F(  7,    62) =    6.52
       Model |  65.6579959     7  9.3797137            Prob > F      =  0.0000
    Residual |  89.1313823    62  1.43760294           R-squared     =  0.4242
-------------+------------------------------           Adj R-squared =  0.3592
       Total |  154.789378    69  2.24332432           Root MSE      =   1.199

------------------------------------------------------------------------------
  mobilcomp3 |      Coef.   Std. Err.      t    P>|t|                     Beta
-------------+----------------------------------------------------------------
      female |  -.4459266   .3270274    -1.36   0.178                -.1408499
         age |   .0029994   .0113316     0.26   0.792                 .0264568
 yesotherinf |   1.137456   .2967131     3.83   0.000                 .3810497
   awareness |   .2110777   .0749571     2.82   0.007                 .2862632
  healthprob |   .2698884   .3079291     0.88   0.384                 .0901525
fresymptoms2 |   .2741217   .1371879     2.00   0.050                 .2240903
    luseoft2 |   .0125463    .006133     2.05   0.045                  .206789
       _cons |  -3.164252   .6823643    -4.64   0.000                        .
------------------------------------------------------------------------------
R-Square Diff. Model 4 - Model 3 = 0.039   F(1,62) =  4.185  p = 0.045


Model  R2      F(df)             p          R2 change  F(df) change       p
   1:  0.022   0.745(2,67)       0.479
   2:  0.300   6.968(4,65)       0.000      0.278     12.926(2,65)       0.000
   3:  0.385   6.582(6,63)       0.000      0.085      4.366(2,63)       0.017
   4:  0.424   6.525(7,62)       0.000      0.039      4.185(1,62)       0.045
```

REFERENCES

ADEY, P. and ANDERSEN, B. (2011) Event and anticipation: UK Civil Contingencies and the space-times of decision. *Environment and Planning A*, 43 (12), pp. 2878–2899.

AGRESTI, A. and FINLAY, B. (2009) *Statistical methods for the social sciences*. 4th ed. Upper Saddle River: Pearson Prentice Hall.

AGUILÉRA, A., GUILLOT, C. and RALLET, A. (2012) Mobile ICTs and physical mobility: Review and research agenda. *Transportation Research Part A*, 46 (4), pp. 664–672.

GOVERNMENT OF THE UNITED KINGDOM (2010) Air quality standards regulations. No. 1001.
Available from: http://www.legislation.gov.uk/uksi/2010/1001/contents/made [Accessed 31st July 2012].

AJZEN, I. (1985) From intentions to actions: A theory of planned behavior. In: KUHI, J. and BECKMANN, J. (eds.) *Actionócontrol: From cognition to behaviour*. Heidelberg: Springer, pp. 11–39.

AJZEN, I. (1991) Theory of planned behaviour. *Organizational Behaviour and Human Decision Making Processes*, 50 (2), pp. 179–211.

ALEXANDER, B. et al. (2011) Anything, anywhere, anytime? Developing indicators to assess the spatial and temporal fragmentation of activities. *Environment and Planning B: Planning and Design*, 38 (4), pp. 678–705.

ALWIN, D.F. and KROSNICK, J.A. (1991) The Reliability of Survey Attitude Measurement. The Influence of Questions and Respondent Attributes. *Sociological Methods and Research*, 20 (1), pp. 139–181.

AMANN, M. et al. (2008) *Health Risks of Ozone from Long-Range Transboundary Air Pollution*. World Health Organization. Available from:
http://www.euro.who.int/__data/assets/pdf_file/0005/78647/E91843.pdf
[Accessed 31st July 2012].

ATKINSON, N.L. and GOLD, R.S. (2002) The promise and challenge of eHealth interventions. American Journal of Health Behaviour, 26 (6), pp. 494–503.

AUSTIN, H.W. (2002) Sample Size: How Much is Enough? In: DE VAUS, D.A. (ed.) *Social Surveys*. London: SAGE, pp. 51–57.

BABBIE, E.R. (2010) *The practice of social research*. 12th ed. London: Wadsworth.

BAGLEY, M.N. and MOKHTARIAN, P.L. (1997) Analyzing the preference for non-exclusive forms of telecommuting: Modeling and policy implications. *Transportation*, 24 (3), pp. 203–226.

BANDURA, A. (1978) The self system in reciprocal determinism. *American Psychologist,* 33 (4), pp. 344–358.

BANDURA, A. (1986) *Social Foundations of Thought and Action: A Social Cognitive Theory*. Englewood Cliffs: Prentice-Hall.

BAUSINGER, H. (1984) Media,Technology and Everyday Life. *Media, Culture and Society*, 6 (4), pp. 343–352.

BECKER, M. (1974) The health belief model and personal health behaviour. *Health Education Monographs*, 2 (4), pp. 324–508.

BERRY, M. and HAMILTON, M. (2010) Changing urban spaces: mobile phones on trains. *Mobilities*, 5 (1), pp. 111–129.

BØHLER, T. et al. (2002) Providing multi-modal access to environmental data–customizable information services for disseminating urban air quality information in APNEE. *Computers, Environment and Urban Systems*, 26 (1), pp. 39–61.

BOULOS, M.N.K. (2004) Towards evidence-based, GIS-driven national spatial health information infrastructure and surveillance services in the United Kingdom. *International Journal of Health Geographics*, 3 (1), p.1.

BRYMAN, A. (1984) The debate about quantitative and qualitative research: A question of method or epistemology? *The British Journal of Sociology*, 35 (1), pp. 75–92.

BRYMAN, A. (2008) *Social research methods*. 3rd ed. Oxford: Oxford University Press.

BRYMAN, A. and CRAMER, D. (1994) *Quantitative data analysis for social scientists*. Rev. ed. London: Routledge.

BULMER, M. (2001) Social measurement: What stands in its way? *Social Research*, 68 (2), pp. 455–480.

CALABRESE, F., LORENZO, G.D. and RATTI, C. (2010) Human Mobility Prediction based on Individual and Collective Geographical Preferences. In: *Proceedings of the 13th International IEEE Annual Conference on Intelligent Transportation Systems*, Madeira Island, 19-22 September 2010.

CLARK, G.L. (2010) Human nature, the environment, and behaviour: Explaining the scope and geographical scale of financial decision-making. *Geografiska Annaler, Series B: Human Geography*, 92 (2), pp. 159–173.

COMMITTEE ON THE MEDICAL EFFECTS OF AIR POLLUTANTS (COMEAP) (2011) *Review of the UK Air Quality Index*. Available from: http://www.comeap.org.uk/images/stories/Documents/Reports/comeap%20review%20of%20the%20uk%20air%20quality%20index.pdf [Accessed 31 July 2012].

COOK, R.D. and WEISBERG, S. (1982) *Residuals and Influence in Regression*. New York: Chapman and Hall.

CRAMER, D. (2003) *Advanced quantitative data analysis*. Maidenhead: Open University Press.

CRONBACH, L.J. (1951) Coefficient alpha and the internal structure of tests. *Psychometrika*, 16 (3), pp. 297–334.

CRONBACH, L.J. and MEEHL, P.E. (1955) Construct validity in psychological tests. *Psychological Bulletin*, 52 (4), pp. 281–302.

DALES, R.E., CAKMAK, S. and Vidal, C.B. (2009) Air pollution and hospitalization for headache in Chile. *American Journal of Epidemiology*, 170 (8), pp. 1057–1066.

DARROW, L.A., KLEIN, M. and FLANDERS, W.D. (2009) Air pollution and preterm birth: A time-series analysis. *Epidemiology*, 20 (5), pp. 689–698.

DELFINO, R.J., ZEIGER, R.S. and SELTZER, J.M. (1998) Symptoms in pediatric asthmatics and air pollution: Differences in effects by symptom severity, anti-inflammatory medication use and particulate averaging time. *Environmental Health Perspective*, 106 (11), pp. 751–761.

DE SOUZA E SILVA, A. (2006) From cyber to hybrid: Mobile technologies as interfaces of hybrid spaces. *Space and Culture*, 9 (3), pp. 261–278.

DE VAUS, D.A. (2002) *Social surveys*. London: SAGE.

DE VAUS, D.A. (2006) *Research design*. London: SAGE.

DIJST, M. (2004) ICT and accessibility: An action space perspective on the impact of new information and communication technologies. In: BEUTHE, M. et al, (eds.) *Transport developments and innovation in an evolving world*. Berlin: Springer, pp. 27–46.

DIJST, M., FARAG, S. and SCHWANEN, T. (2008) A comparative study of attitude theory and other theoretical models for understanding travel behaviour. *Environment and Planning A*, 40 (4), pp. 831–847.

DOMINICI, F. et al. (2006) Fine particulate air pollution and hospital admission for cardiovascular and respiratory diseases. *Journal of the American Medical Association*, 295 (10), pp. 1127–1134.

EUROPEAN UNION (2008) *Directive 2008/50/EC on ambient air quality and cleaner air for Europe*. Available from: http://eurlex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2008:152:0001:0044:EN:PDF [Accessed 31st July 2012].

FARAG, S. et al. (2007) Shopping online and/or in-store? A structural equation model of the relationships between e-shopping and in-store shopping. *Transportation Research A*, 41 (2), pp. 125–141.

FERRELL, C.E. (2005) Home-based teleshopping and shopping travel: Where do we find the time? *Transportation Research Record 1926*, pp. 212–223.

FJELDSOE, B.S., MARSHALL, A.L. and MILLER, Y.D. (2009) Behavior Change Interventions Delivered by Mobile Telephone Short-Message Service. *American Journal of Preventive Medicine*, 36 (2), pp.165–173.

FRICKER, R.D., Jr. (2008) Sampling methods for web and e-mail surveys. In: FIELDING, N., LEE, M.R. and BLANK, G. (eds.) *The SAGE Handbook of Online Research Methods*. London: SAGE, pp. 195–216.

GASKELL, G.D., O'MUIRCHEARTAIGH, C.A. and WRIGHT, D.B. (1994) Survey questions about the frequency of vaguely defined events: The effects of response alternatives. *Public Opinion Quarterly*, 58 (2), pp. 241–254.

GAUDERMAN, W.J. et al. (2004) The effect of air pollution on lung development from 10 to 18 years of age. *The New England Journal of Medicine*, 351 (11), pp. 1057–1067.

GOODCHILD, M.F. and CARLEY, K.M. (2010) *Spatio-temporal constraints on social networks*. National Center for Geographic Information and Analysis, Santa Barbara, 13-14 December, 2010. Available from http://www.ncgia.ucsb.edu/projects/spatio-temporal [Accessed 31st July 2012].

GOULD, J. and GOLOB, T. (1997) Shopping without travel or travel without shopping? An investigation of electronic home shopping. *Transportation Reviews*, 17 (4), pp. 355–376.

GRAHAM, M. (2010) Neogeography and the palimpsests of place: Web 2.0 and the construction of a virtual Earth. *Tijdschrift voor Economische en Sociale Geografie*, 101 (4), pp. 422–436.

GRAHAM, S. and MARVIN, S. (1996) *Telecommunications and the City: Electronic Spaces, Urban Places*. London: Routledge.

GREEN, N. and HADDON, L. (2009) *Mobile communications: An introduction to new media*. New York: Berg.

GREEN, L. (2010) *The Internet. An introduction to new media*. Oxford: Berg.

HADDON, L. (2004) *Information and communication technologies in everyday life: A concise introduction and research guide*. Oxford: Berg.

HADDON, L. (2007) Roger Silverstone's legacies: domestication. New Media Society, 9 (1), pp. 25–32.

HALKO, S. and KIENTZ, J.A. (2010) Personality and persuasive technology: An exploratory study on health-promoting mobile applications. In: PLOUG, T., HASLE, P. and OINAS-KUKKONEN, H. (eds.) Persuasive Technology. Proceedings of the 5th International Conference, PERSUASIVE 2010, Copenhagen, June 7-10, 2010. Berlin: Springer, pp. 150–161.

HAMILTON, L.C. (2009) *Statistics with Stata: Updated for version 10*. Belmont: Cengage Learning.

HARDY, M.A. and BRYMAN, A. (2009) *Handbook of data analysis*. Rev. ed. London: SAGE.

HEWSON, C. and LAURENT, D. (2008) Research design and tools for Internet research. In: FIELDING, N., LEE, R.M. and BLANK, G. (eds) *Online Research Methods*. London: SAGE, pp. 58-78.

HIPÓLITO, J.F. (2007) Multimedia mobile services with applications in environment. *Technological Forecasting & Social Change*, 74 (6), pp. 854–865.

HITCHINGS, R. (2011) Researching air-conditioning addiction and ways of puncturing practice: Professional office workers and the decision to go outside. *Environment and Planning A*, 43 (12), pp. 2838–2856.

HJORTH, L. (2009) The big bang: An example of mobile media as new media. *Computers in Entertainment (CIE)*, 7 (2), pp.1–13.

HOBSON, D. (1980) Housewives and the Mass Media. In HALL, S. et al, (eds.) *Culture, Media, Language*. London: Hutchinson, pp. 105–14.

HÖFLICH, J.R. (2005a) The mobile phone and the dynamic between private and public communication: Results of an international exploratory study. *Knowledge, Technology and Policy*, 19 (2), pp. 58–68.

HÖFLICH, J.R. (2005b) A Certain Sense of Place. In: NYÍRI, J.K. (ed.) *A Sense of Place: The Global and the Local in Mobile Communication*. Vienna: Passagen Verlag, pp. 159–168.

HOLLOWAY, T., KINNEY, P.L. and SAUTHOFF, A. (2005) Application of air quality models to public health analysis. *Energy for Sustainable Development*, 9 (3), pp. 49-57.

HUOMO, H. (2001) Applications are the drivers in the mobile information society. *Wireless Personal Communications*, 17 (2-3), pp. 337–341.

INTERNATIONAL TELECOMMUNICATION UNION (ITU) (2011) *Facts and Figures*. Available from: http://www.itu.int/ITU-D/ict/facts/2011/material/ICTFactsFigures2011.pdf [Accessed 31st July 2012].

JUDD, C.M. and KENNY, D.A. (2006) Research Design and Research Validity. In: DE VAUS, D.A. (ed.) *Research design*. London: SAGE, pp. 101–119.

KAHNEMANN, D. (2003) Maps of bounded rationality: Psychology for behavioral economics. *The American Economic Review*, 93 (5), pp. 1449–1475.

KELLY, F.J. et al. (2012) Monitoring air pollution: Use of early warning systems for public health. Official Journal of the Asian Pacific Society of Respirology, 17 (1), pp. 7–19.

KENYON, S., LYONS, G. and RAFFERTY, J. (2002) Transport and social exclusion: Investigating the possibility of promoting inclusion through virtual mobility. *Journal of Transport Geography*, 10 (3), pp. 207–219.

KIDDER, L. (1981) *Selltiz, Wrightsman, and Cook's - Research methods in social relations*. 4th ed. New York: Holt, Rinehart & Winston.

KNOKE, D., BOHNSTEDT, G.W. and MEE, A.P. (2002) *Statistics for social Data analysis*. 4th ed. Belmont: Wadsworth.

KOLAKOWSKI, L. (1972) *Positivist philosophy from Hume to the Vienna Circle.* Harmondsworth: Penguin.

KOPOMAA, T. (2000) *The city in your pocket: Birth of the mobile information society*. Helsinki: Gaudeamus.

KUMAR, P. et al. (2011) Dynamics and dispersion modelling of nanoparticles from road traffic in the urban atmospheric environment - A review. *Journal of Aerosol Science*, 42 (9), pp. 580–603.

KWAN, M.-P. (2002) Time, information technologies and the geographies of everyday life. *Urban Geography*, 23 (5), pp. 471–482.

KWAN, M.-P. (2006) Transport geography in the age of mobile communications. *Journal of Transport Geography*, 14 (5), pp. 384–385.

KWAN, M.-P., DIJST, M. and SCHWANEN, T. (2007) The interaction betweenICT and human activity-travel behavior. *Transportation Research Part A*, 41 (2), pp.121–124.

LIANG, W., WEI, H. and KUO, H. (2009) Association between daily mortality from respiratory and cardiovascular diseases and air pollution in Taiwan. *Environmental Research*, 109 (1), pp. 51–58.

LIE, M. and SØRENSEN, K. (eds.) (1996) *Making technologies our own? Domesticating technology into everyday life*. Oslo: Scandinavian University Press.

LINE, T., JAIN, J. and LYONS, G. (2011) The role of ICTs in everyday mobile lives. *Journal of Transport Geography*, 19 (6), pp. 1490–1499.

LONDON AIR QUALITY NETWORK (LAQN) (2012) *London Air*. Environmental Research Group, King's College London.
Available from: http://www.londonair.org.uk/LondonAir/apps.aspx [Accessed 31st July 2012].

LULL, J. (1988) *World families watch television*. Newbury Park: SAGE.

MacELROY, B. (2002) Measuring response rates in online surveys. In: DE VAUS, D.A. (ed.) *Social Surveys*. London: SAGE, pp. 182–184.

MARSH, C. (2002) Problems with Surveys: Method or Epistemology? In: DE VAUS, D.A. (ed.) *Social Surveys*. London: SAGE, pp. 93–109.

McCORMACK, D.P. and SCHWANEN, T. (2011) The space – times of decision making. *Environment and Planning A*, 43(12), pp. 2801–2818.

McDERMOTT, M., SRIVASTAVA, R. and CROSKELL, S. (2006) Awareness of and compliance with air pollution advisories: A comparison of parents of asthmatics with other parents. *Journal of Asthma*, 43 (3), pp. 235–239.

MIDDLETON, J. (2011) I'm an autopilot, I just follow the route: Exploring the habits, routines, and decision-making practices of everyday urban mobilities. *Environment and Planning A*, 43 (12), pp. 2857–2877.

MISTRY, P. (2012) *SixthSense – Integrating information with the real world*. MIT Media Lab. Available from: http://www.pranavmistry.com/projects/sixthsense/ [Accessed 31st July 2012].

MOKHTARIAN, P.L., HANDY, S.L. and SALOMON, I. (1995) Methodological issues in the estimation of travel, energy, and air quality impacts of telecommuting. *Transportation Research A*, 29 (4), pp. 283–302.

MOKHTARIAN, P.L. and MEENAKSHISUNDARAM R. (1999) Beyond tele-substitution: Disaggregate longitudinal structural equations modeling of communication impacts. *Transportation Research C*, 7 (1), pp. 33–52.

OFFICE FOR NATIONAL STATISTICS (ONS) (2011) *Internet access – households and individuals*. Available from: http://www.ons.gov.uk/ons/dcp171778_227158.pdf [Accessed 31st July 2012].

OPPENHEIM, A. N. (2000) *Questionnaire design, interviewing and attitude measurement*. New ed. London: Continuum.

PAVLOV, I.P. (1897) *The work of the digestive glands*. Translated by W.H. Thompson, 1902. London: Griffin.

PRED, A. (1967) *Behaviour and location. Foundation for a geographic and dynamic location theory*. Part I. Lund studies in geography, series B, 27. Lund: C.W.K. Gleerup.

PROCHASKA, J.O. and Di CLEMENTE, C.C. (1986) Towards a comprehensive model of change. In: MILLER, W.R. and Heather, N. (eds.) *Treating addictive behaviours: Processes of change*. NewYork: Plenum Press, pp. 3–27.

PUNCH, K. (2005) *Introduction to social research: quantitative and qualitative approaches*. 2nd ed. London: SAGE.

RATTI, C. et al. (2011) *Senseable City Guide*. The SENSEable City Lab at the Massachusetts Institute of Technology. Cambridge, Massachusetts: SA+P Press.

REN, F. and KWAN, M.-P. (2007) Geovisualization of human hybrid activity–travel patterns. *Transactions in GIS*, 11 (5), pp. 719–742.

REN, F. and KWAN, M.-P. (2009) The impact of the Internet on human activity–travel patterns: Analysis of gender differences using multi-group structural equation models. *Journal of Transport Geography*, 17 (6), pp. 440–450.

RESCH, B. et al. (2011) Standardised geo-sensor webs for integrated urban air quality monitoring. In: EKUNDAYO, E.O. (ed.) Environmental Monitoring. Rijeka: InTech, pp. 513–528.

RESCH, B., BRITTER, R., and RATTI, C. (2012) Live Urbanism – Towards Senseable Cities and Beyond. In: PARDALOS, P. and RASSIA, S. (eds.) *Sustainable Architectural Design: Impacts on Health*. New York: Springer, pp. 175–184.

RØPKE, I. (2001) New technology in everyday life – social processes and environmental impact. *Ecological Economics*, 38 (3), pp. 403–422.

ROSENLUND, M. et al. (2006) Long-term exposure to urban air pollution and myocardial infarction. *Epidemiology*, 17 (4), pp. 383–390.

SALOMON, I. (1986) Telecommunications and travel relationships: A review. *Transportation Research Part A: General*, 20 (3), pp. 223–238.

SCHILDCROUT, J.S. et al. (2006) Ambient air pollution and asthma exacerbations in children: An eight-city analysis. *American Journal of Epidemiology*, 164 (6), pp. 505–517.

SCHLINK, U. et al. (2010) Evaluation of human mobility models, for exposure to air pollutants. *Science of the total environment*, 408 (18), pp. 3918–3930.

SEMENZA, J.C., WILSON, D.J. and PARRA, J. (2008) Public perception and behavior change in relationship to hot weather and air pollution. *Environmental Research*, 107 (3), pp. 401–411.

SILVERSTONE, R. and HADDON, L. (1996) Design and the domestication of information and communication technologies: Technical Change and Everyday Life. In SILVERSTONE, R. and MANSELL, R. (eds.) *Communication by Design: The Politics of Information and Communication Technologies*. Oxford: Oxford University Press, pp. 44–74.

SILVERSTONE, R., HIRSCH, E. and MORLEY, D. (1992) Information and communication technologies and the moral economy of the household. In: SILVERSTONE, R. and HIRSCH, E. (eds.) *Consuming technologies: Media and information in domestic spaces*. London: Routledge, pp.115–31.

SIMON, H. (1959) Theories of decision-making in economics and behavioural science. *The American Economic Review*, 49 (3), pp. 252–283.

SKINNER, B.F. (1938) *The behavior of organisms: An Experimental Analysis*. New York: Appleton-Century-Crofts.

SOCIAL RESEARCH ASSOCIATION (SRA) (2003) *Ethical guidelines*. Available from: http://www.the-sra.org.uk/guidelines.htm [Accessed 31st July 2012].

SOLOW-NIEDERMAN, A. et al. (2012) *Final Briefing Document: Public Networks for Public Safety: A Workshop on the Present and Future of Mesh Networks*. Harvard: Berkman Center for Internet & Society, research publication no. 2012–12. Available from: http://cyber.law.harvard.edu/publications/2012/public_networks_for_public_safety [Accessed 31st July 2012].

STIEB, D. et al. (2009) Air pollution and emergency department visits for cardiac and respiratory conditions: A multi-city time-series analysis. *Environmental Health*, 8 (1), p. 25.

STOUFFER, S.A. (2002) Some Observations on Study Design. In: DE VAUS, D.A. (ed.) *Social Surveys*. London: SAGE, pp. 255–264.

STRICKLAND, M.J. et al. (2010) Short-term associations between ambient air pollutants and pediatric asthma emergency department visits. *American journal of respiratory and critical care medicine*, 182 (3), pp. 307–316.

SUDMAN, S. and BLAIR, E. (2002) Sampling in the twenty-first century. In: DE VAUS, D.A. (ed.) *Social Surveys*. London: SAGE, pp. 284–285.

THORNDIKE, E.I. (1905) *The elements of psychology*. New York: Seiler.

TIMMERMANS, H., ARENTZE, T. and JOH, C.-H. (2002) Analysing space-time behaviour: new approaches to old problems. *Progress in Human Geography*, 26 (2), pp. 175–190.

TIMMERMANS, H. and GOLLEDGE, R.G. (1990) Applications of behavioural research on spatial problems II: preference and choice. *Progress in Human Geography*, 14 (1), pp. 311–354.

U.S. Environmental Protection Agency (USEPA) (2011) *Final Report. The benefits and costs of the clean air act from 1990 to 2020.* Available from: http://www.epa.gov/oar/sect812/feb11/fullreport.pdf [Accessed 31st July 2012].

VEHOVAR, V. and MANFREDA, K.L. (2008) Overview: Online Surveys. In: FIELDING, N., LEE, R.M. and BLANK, G. (eds.) *The SAGE Handbook of Online Research Methods*. London: SAGE. pp. 177–194.

WARWICK, D. P. and LININGER, C.A. (1975) *The Sample Survey: Theory and Practice.* New York: McGraw-Hill.

WATSON, J.B. (1913) Psychology as the behaviorist views it. *Psychological Review*, 20 (2), pp. 158–177.

WEN, X.-J., BALLUZ, L. and MOKDAD, A. (2009) Association between media alerts of air quality index and change of outdoor activity among adult asthma in six states, BRFSS, 2005. *Journal of Community Health*, 34 (1), pp. 40–46.

WETCHER-HENDRICKS, D. (2011) *Analyzing quantitative data: An introduction for social researchers*. Hoboken: Wiley.

WILKINSON, L., BLANK, G. and GRUBER, C. (1996) *Desktop Data analysis with SYSTAT.* London: Prentice-Hall.

WILSON, M.W. (in press) Location-based services, conspicuous mobility, and the location-aware future. *Geoforum*. (Accepted for publication in the next issue).

YIM, S.H.L. and BARRETT, S.R.H. (2012) Public Health Impacts of Combustion Emissions in the United Kingdom. *Environmental Science and Technology*, 46 (8), pp. 4291–4296.

YOSHII, T. and SASAKI, K. (2010) Information/Communication Technologies and travel behaviour. *Transportation Research Part C: Emerging Technologies*, 18 (1), pp. 1–2.