

Exploring spatial and temporal variation in perception of crime and place using crowdsourced data

Reka Solymosi

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Department of Security and Crime Science
University College London

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I, Reka Solymosi, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the work.

Abstract

To advance and widen the scope of research into the perception of crime and place, innovations in technology for data collection can be utilized as research tools. To date, there has been little exploration into these new methods of data capture.

This thesis presents the possibilities of using crowdsourced data collection methods for application to research in environmental criminology. The lack of detailed data on people's experiences and movements at a micro geographical and temporal resolution have impeded the exploration of many of the subtleties of the relationship between crime and place, but this data-gap can be filled by creatively applying new technologies for data collection.

The core chapters in this thesis give empirical examples, which demonstrate that spatiotemporal data on people's experiences with crime and disorder during their routine activities can be collected and used to study perception of crime and place. By exploring such crowdsourced data from an environmental criminology framework, I demonstrate how fear of crime varies in place and time, dynamically within individuals, which is not reflected in current measurement approaches. I also propose crowdsourced collection of volunteered geographic information as a proxy measurement for within-day fluctuations for active guardianship, possibly highlighting areas of temporarily increased crime risk. Such information also shows promise in identifying when people are likely to encounter signal disorders as part of their everyday routine activities, leading to possible experiences of fear of crime.

These findings provide novel insight into fear of crime, signal disorders, and active guardianship, which allows for the exploration of these concepts as situation-dependent, dynamic experiences. Theoretical development of this

thesis is the application of the framework of environmental criminology to the study of subjective perceptions, and the possibility to gather empirical data to support this approach is made possible by the methodological developments presented within. This approach serves as a guideline for studying perception in a way that allows for situational prevention measures to be introduced. Making use of new insight into dynamic variation in context allows for identification of areas with temporarily increased risk of crime, disorder or fear of crime. This thesis contributes to theoretical and methodological growth in the study of perception of crime and place by applying crowdsourcing theory and practice to its measurement.

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Contents

1	Introduction	23
1.1	Thesis structure	25
1.1.1	Chapter 2: Theoretical framework	25
1.1.2	Chapter 3: Methodological framework	25
1.1.3	Chapters 4, 5, and 6: Crowdsourcing data on routine activities	26
1.1.4	Chapters 7 and 8: Mobile technologies and surveying fear of crime	27
1.1.5	Chapter 9: Discussion	28
1.2	Overview	29
2	Theoretical Background	31
2.1	Crime and its environment	32
2.1.1	Rational Choice Theory	33
2.1.2	Crime Pattern Theory	35
2.1.3	Routine Activities Theory	35
2.1.4	Ecology of crime models	37
2.1.5	Crime and its environment	38
2.2	The importance of perceptions of crime	39
2.2.1	Definition(s) of fear of crime	42
2.2.2	Fear of crime is situational	44
2.2.3	Measuring fear of crime	45
2.2.4	Spatial resolution of fear of crime	50
2.2.5	Fear of crime as a context-dependent everyday experience	52

2.3	Signal disorders - Environmental correlates of fear of crime . . .	53
2.3.1	Measuring signal disorders	55
2.4	Active Guardianship of Place	58
2.4.1	Measuring active guardianship	58
2.5	Gap in the literature: dynamic measurements	61
3	Methodological Framework	63
3.1	New technologies and new data sources	64
3.2	Crowdsourcing: harnessing the power of the many	68
3.3	Crowdsourced data for research	71
3.3.1	Crowdsourced data for academic research	71
3.3.2	Crowdsourced data for crime research	73
3.3.3	Applications for perception of crime and place	74
3.3.4	Advantages and limitations	76
3.4	Bespoke data collection using new technologies	78
3.4.1	Methodologies behind using new technologies for crowd- sourced data collection for research	79
3.4.2	Advantages and limitations	81
3.5	Applying methodological framework to measure perception of crime and place	82
3.6	Notes on data and unit of analysis for throughout this thesis . . .	83
3.6.1	Data	83
3.6.2	Spatial unit of analysis	87
4	Understanding crowdsourced problem reporting data	89
4.1	Fix My Street	89
4.2	Assumptions	93
4.2.1	Accuracy of spatial information	93
4.2.2	Is the temporal information with the report a reflection of when people encounter the issues they report?	95
4.3	Reporting behaviour: the Who and the What	97
4.4	Discussion	102

5	A dynamic measure for active guardianship	105
5.1	Bodies on the street versus eyes on the street	106
5.2	Measuring active guardianship using FMS	107
5.2.1	Analytical approach	109
5.3	Willingness to intervene	110
5.4	Fluctuation in crime risk	113
5.5	Discussion	120
6	A dynamic measure of disorder	123
6.1	Testing different measures of disorder	124
6.1.1	Data and study area	124
6.1.2	FMS complaints and all council complaints	127
6.1.3	Complaints, SSO, and questionnaire measures of disorder	130
6.2	Complaints and the fear of crime	135
6.3	Exploring experience with disorder in place and time	141
6.4	Between group differences in experience with disorders	147
6.5	Discussion	153
7	Developing a tool for a dynamic measure of fear of crime	157
7.1	Fear of crime application prototype development	158
7.1.1	Putting fear of crime (experience) on the map	159
7.1.2	Questionnaire development	162
7.2	Building the Fear of Crime Application	166
7.3	Initial changes and application testing	176
7.3.1	Changes to ensure spatial and temporal accuracy	176
7.3.2	Pilot testing the application	181
7.4	Ethics	186
7.5	Discussion	188
8	Fear of crime as a context-dependent experience	191
8.1	Study design	192
8.2	Study sample	193
8.3	Descriptive analysis of within-person fluctuation in fear	196

8.4	Co-variates of fear	205
8.4.1	Methods for analysis	206
8.4.2	Results	207
8.5	Applications and impact	214
8.5.1	Mapping fear of hate crime in Camden	215
8.5.2	Mapping fear of crime on an East London bus route . . .	216
8.6	Discussion	222
9	Discussion	227
9.1	Limitations	228
9.2	Summary of findings	230
9.3	Discussion of new insight gained	234
9.4	Future work	237
9.5	Implications for policy and practice	239
9.6	Final summary	240
	Bibliography	243

List of Figures

2.1	Crime triangle, from Clarke and Eck (2014)	36
2.2	Fear of crime articles in top criminology journals	40
2.3	Word cloud from the abstracts of the pool of 1301 fear of crime papers	43
4.1	Overarching categories FMS reports fit into.	90
4.2	Number of reports submitted via FMS per year (2015 only up to January)	91
4.3	Number of internet users per year	92
4.4	Map to highlight the extent to which councils that adopt FMS are overrepresented in reports compared to all others	93
4.5	Temporal trends in reporting reflects daily cycle in all activities	94
4.6	Percentage of all FMS reports about street lights.	96
4.7	Lorenz curve of FMS participation	99
4.8	Number of FMS reports per neighbourhood by IMD score	102
5.1	Data for measuring active guardianship	108
5.2	Change in active guardianship and population between day and nighttime	119
6.1	Scatterplot of neighbourhoods by number of FMS reports and all council complaints	128
6.2	Complaints reported in total to Camden vs those reported via FMS only	129
6.3	Complaints of rubbish vs perceived and observed levels	134
6.4	Perceived rubbish and fear of crime	139

6.5	Percentage of all FMS reports about incivilities.	142
6.6	FMS report about 'over flowing rubbish, street drinkers, litter in the street and rats'	144
6.7	Gi* map of FMS reports that are incivilities	145
6.8	Variation in hotspots of signal crimes within the day	146
6.9	Proportion of FMS reports that are about incivilities by gender during hours of the day	149
6.10	Hotspots of incivility reports with FMS in central London area by gender	150
6.11	Chi-square standardised residual table of number of reports in FMS categories by gender (anything greater than 2 or below -2 is a meaningful difference)	152
7.1	Sticker map from participatory mapping of fear or crime exercise	161
7.2	Piloting app questions using EpiCollect	163
7.3	FOCApp initial screenshots	169
7.4	Validity checks on free text responses	170
7.5	FOCApp main page screenshots	173
7.6	Final page of application presenting choices for reason for fear of crime	174
7.7	Flow chart illustrating process of FOCApp	175
7.8	Simulations of participants over 2 week period	178
7.9	Simulations of participants over 4 week period	179
7.10	Fear of crime map for one participant	183
7.11	Fear of crime map for 6 participants	184
8.1	FOCApp downloads from Google Play Statistics	192
8.2	Reports sent by each participant over course of study	194
8.3	Lorenz curve for FOCApp participants	196
8.4	Most participants sent at least 2 reports and the majority of them showed fluctuation in fear of crime levels during the study	197
8.5	Time series of reports from one participant (fear of crime scores converted to numbers)	198

8.6 Time series of reports from people with significant interdependence between observations (fear of crime scores converted to numbers) 200

8.7 Overview map of FOCAApp reports by all participants 202

8.8 Variation in fear of crime across days of the week 203

8.9 Variation in fear of crime across hours of the day 204

8.10 Subject effects via conditional modes with 95% confidence intervals based on the conditional variance 212

8.11 Distribution of fear of crime reports within participants 214

8.12 Changes to FOCAApp 217

8.13 Changes to application for use by TfL as Bus app 219

8.14 RPI trial of measuring fear of crime along bus route 220

8.15 Fear of crime along bus route on board the bus vs at stop 220

List of Tables

5.1	Model 1: Willingness to intervene in neighbourhood vs burglary rate	116
5.2	Model 2: Willingness to intervene and daytime population change in neighbourhood vs burglary rate	116
5.3	Model 3: Willingness to intervene and daytime population change and active guardianship change in neighbourhood vs burglary rate	116
5.4	Model 4: Willingness to intervene and active guardianship change in neighbourhood vs burglary rate	116
6.1	Spatial error regression model results for different measures of disorder	131
6.2	Spatial Error Regression Model Results for worry about crime . . .	137
8.1	Chi-square results for variables against fear of crime	208
8.2	Chi-square standardised residuals darkness v fear of crime . . .	208
8.3	Chi-square standardised residuals home neighbourhood v fear of crime	209
8.4	Results from cumulative link model for fear of crime	209
8.5	Results from cumulative link model for fear of crime without age .	210
8.6	Model with only situational predictor variables	210
8.7	Result of likelihood ratio test	211
9.1	Summary of novel data collection approaches in this thesis . . .	231
9.2	Summary of novel data collection approaches in this thesis (contd.)	232

Context

Context for this research

The research presented in this thesis can be considered to fall within the discipline of crime science. Crime science is "the application of the methods of science to crime and disorder" (Laycock), and the approach of this thesis is to apply the methods of science to *perception* of crime and disorder. The range of disciplines from which I draw for methods is vast and includes Geography, Psychology, Sociology, Epidemiology, Economics, and the newly emerging area of Social Data Science. However, I do not only borrow, but also feed back into these disciplines, furthering the application of their methods through applying them to the study of crime and place. The results of my research have been disseminated across conferences that cover data management, transport geography, and criminology, and have been applicable for practitioners in transport and in community safety activism. A summary list of the dissemination of results from this thesis is as follows:

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- R. Solymosi, "Measuring perceptions of safety and fear of crime in everyday life", UCL Sensing Environments Network Bimonthly Seminar Series May 2015
- R. Solymosi, "Mapping Fear of Crime Dynamically in Place and Time: Case study of Revenue Protection Inspectors on a London Bus Route," American Society of Criminology, San Francisco, USA, Nov 2014.
- R. Solymosi, "Using a smartphone app to report fear of hate crime," Trans London Meetup, London, UK, Oct 2014.
- R. Solymosi, "Using a smartphone app to measure fear of crime on route 25," Transport for London Route 25 Joint Transport Action Group (JTAG) meeting, London, UK, Sep 2014.
- R. Solymosi, "Fear of crime on transport," PopFest - The Population Studies Conference, London, UK, Aug 2014.
- R. Solymosi, "A new approach to mapping perceptions of crime along the door-to-door journey," Transport Geography Research Group Workshop, Leeds, UK, Apr 2014.

- R. Solymosi, "Mapping fear of crime as a dynamic event," Streets, Crime, and Transport, London, UK, Feb 2014.
- R. Solymosi, "Participatory mapping of fear of crime using a mobile phone application," Urban Data Management Symposium, London, UK, May 2013.

Poster presentations:

- R. Solymosi, "Mapping fear of crime hotspots as they vary with place, time, and individual characteristics using a mobile phone app," Home Office International Crime and Policing Conference, London, UK, Jan 2015.
- R. Solymosi, "Mapping fear of crime,"EuroCrim2013 European Society of Criminology Conference, Budapest, Hungary, Aug 2013.
- R. Solymosi, "Mapping fear of crime as a dynamic event," International Crime Science Conference, London, UK, Jul 2012.

Chapter 1

Introduction

To advance and widen the scope of research into the perception of crime and place, innovations in technology for data collection can be utilised as research tools. To date, there has been little exploration of these new methods of data capture.

This thesis presents the possibilities of using novel data collection methods through adopting emerging technologies and making use of crowdsourced data for application to research in environmental criminology. The lack of detailed data on people's experiences and movements at a micro-geographical (i.e. resolutions finer than neighbourhood level) and temporal (i.e. finer than a dichotomy between daytime and after dark) resolution have impeded the exploration of many of the subtleties of the relationship between perception of crime and place, but this data gap can be filled by creatively applying new technologies for data collection.

The core chapters of this thesis (Chapters 4, 5, 6, 7, and 8) give empirical examples, which demonstrate that, through new techniques, spatiotemporal data on people's experiences, perceptions, and behaviour in response to crime and disorder during their routine activities can be collected and used to study the perception of crime and place within an environmental criminology framework. By exploring new data sources through these examples, I demonstrate how fear of crime varies in place and time, dynamically within individuals. This variation is not captured by current measurement approaches. Finding out for example when and where people are more likely to experience fear of crime incidents can help to inform targeted interventions to reduce the fear of crime.

I propose crowdsourced collection of volunteered geographic information as a way to measure within-day fluctuations for active guardianship, possibly highlighting areas of temporarily increased crime risk, and for identifying when people are likely to encounter signal disorders as part of their everyday routine activities, leading to possible experiences of fear of crime.

These findings provide novel insight into people's dynamic experiences with fear of crime, signal disorders, and active guardianship while serving as an example for applying these approaches to measurement and data collection in criminology research. In Chapters 2 and 3 in this thesis, I argue that lack of innovation in terms of measurement at such small spatial and temporal scale has impeded theoretical progress in this area. Prior research in this field has a tendency to see the fear of crime as a personal attribute rather than a varying state, depending on the environmental context. Similarly, while varying levels of active guardianship have been conceptualised, the dynamic fluctuation with this concept remains elusive for data collection. And finally, *signal* disorder, while understood as an instance of disorder being subjectively perceived as a signal of wider problems, has been measured either by surveys or observation studies. Neither of these approaches reflects the *situational* experience that individuals have when they encounter signal disorders in their everyday routine activities. In this thesis I present evidence to demonstrate that it is possible to collect data about these concepts in a way that reflects their variation over place and time, dependent on the environmental context.

This chapter will briefly describe the structure of the thesis, and detail the contribution of each chapter, as well as the research questions that I answer within. This is intended to provide a brief overview of the framework and contributions proposed. The overall aim is to develop and propose two new approaches to collecting data about people's everyday experiences with crime and place and applying it to test research questions about fear of crime, signal disorders, and active guardianship. By trialling and evaluating two distinct measures, this thesis helps to set the stage for future work using new data collection methods to study fear of crime and perception of place from an environmental criminology framework.

1.1 Thesis structure

1.1.1 Chapter 2: Theoretical framework

Chapter 2 presents the theoretical framework that this thesis works within. It serves to anchor the approach taken for studying the spatial and temporal variation in perception of crime and place throughout this thesis. I emphasise the importance of situational factors associated with increased risk for crime opportunities to occur. To be able to study what these factors are and their relationship with crime, researchers need information about how potential victims and potential offenders spend their time, and what places they visit as part of their daily activities. Therefore, this chapter highlights the theoretical importance of being able to collect data about these routine activities and people's experiences as they go about them. It reasons that to understand how situational factors influence people's subjective perceptions, it is important to learn about these experiences as part of their everyday routine activities.

1.1.2 Chapter 3: Methodological framework

One challenge with framing the study of the perception of crime and place from a situational approach comes from the availability of adequate data. It is a non-trivial task to gather data about the everyday activities of people. Chapter 3 will discuss traditional ways of collecting data about fear of crime and perceptions of disorder, and highlight some key issues with using such data to explore perception as a situation-dependent everyday experience. It will then lay out the potential of novel sources of data in addressing this gap. Specifically, two different approaches will be explored in detail. The first approach is to make use of already available crowdsourced data on people's everyday interactions with their environments and combine multiple data sources to make inferences about routine activities, and their link to crime and associated constructs, such as active guardianship, signal disorders, and the fear of crime. 'Crowdsourcing', a portmanteau of 'crowd' and 'outsourcing', will be introduced as a means for tapping into group intelligence on large scales. The chapter will focus on the applicability of crowdsourcing to research in social sciences, and in par-

ticular the study of crime. The second approach details a method for utilising advances in technology and sensing to develop bespoke surveys that record spatial and temporal information, while querying participants about their perceptions. This method is introduced as a new measurement tool, which builds on the crowdsourcing ethos.

Both methodological approaches will be described in detail, with examples from criminology and other disciplines, followed by possible applications to the study of perception of crime and place.

1.1.3 Chapters 4, 5, and 6: Crowdsourcing data on routine activities

Chapters 4, 5, and 6 discuss the potential of using crowdsourced data to map dynamic fluctuations in crime-related concepts as a result of gaining insight into different elements of people's routine activities. Chapter 4 introduces in detail the data set of crowdsourced complaints about environmental issues. It describes both the rationale and the methods behind its acquisition, cleaning, and structuring, required to be usable for research. I discuss the assumptions that must be made about this data and present evidence to support these assumptions, as well as discussing some of the persisting data limitations.

Chapters 5, and 6 present two case studies for applying this data to explore two different criminological concepts. Chapter 5 details the extent to which these data reflect the presence of active guardians in an area (people who are both willing and capable of intervening to prevent a crime), and whether this can be used to map temporary fluctuation in associated crime risk between neighbourhoods. Chapter 5 answers the following two research questions:

- Can the crowdsourced data identify neighbourhoods with higher levels of willingness to intervene?
- Does short-term absence of active guardians (measured with crowdsourced data) show a negative relationship with crime?

Importantly, Chapter 5 emphasises how crowd participation in such problem reporting platforms shows a distinct variable from just population estimates.

Chapter 6 focuses on reports of environmental anti-social behaviour to map people's experiences with a particular incarnation of signal disorders as they move about in their environments. Here the following research questions are addressed:

- Do the number of environmental complaints about rubbish reflect perceived levels of this issue?
- Do the number of environmental complaints about rubbish reflect observed levels of this issue?
- Do higher proportion of incivilities reported come from areas with higher levels of fear of crime?
- Do opportunities to encounter signal disorders vary in place and time?
- Do experiences with disorders vary between different groups?

Implications of the findings will then be discussed, as well as the limitations of using this data. The chapter will conclude with recommendations for further work to explore the use of crowdsourced data for crime research.

1.1.4 Chapters 7 and 8: Mobile technologies and surveying fear of crime

Another approach to using advances in information technology to collect data about crime-related constructs is to apply these to data collection methodologies, rather than to search for already available data. Chapters 7 and 8 describe the development and implementation of a bespoke data collection tool for a specific research project as a solution to mitigate some of the limitations of the openly available data used in Chapters 4, 5, and 6. By creating bespoke data collection tools, researchers can ensure all data required for a project can be collected, and assumptions can be kept to a minimum.

Specifically, Chapters 7 and 8 present the process of applying bespoke questionnaires to a mobile phone application, in order measure fear of crime longitudinally. This method makes use of the phone's built-in sensors to increase the accuracy of spatial and temporal information collected. Chapter 7

discusses the rationale for, and the methods and practicalities of developing a research tool to facilitate this. Initial results from pilot testing are presented to affirm that this tool is measuring fear of crime in accordance with the theoretical framing set out in this thesis. Chapter 8 takes an in-depth look into the data, to explore both within- and between-person variation in fear of crime, and discuss the link with past research into the field. The research questions addressed by this chapter are:

- Does fear of crime vary within an individual?
- What can spatiotemporal analysis of perceptions reveal about the covariates of fear of crime?

I conclude by presenting fear of crime from this new angle, in line with recent developments in fear of crime research, that is moving towards exploring it as something that fluctuates with place and time, rather than a static attribute. Limitations of the approach are also discussed, as well as possible applications for practitioners to gain a better understanding of difficult-to-measure issues.

1.1.5 Chapter 9: Discussion

The discussion will summarise the contribution of this thesis, in presenting new approaches to research into the subjective perceptions of crime and place. This chapter serves to emphasise that by framing people's experiences as something that is dependent on the situational context, novel insights into these concepts can be gained.

In the same way that a spatial approach was applied to crime research in the past few decades, this thesis explores alternative measurements of perception of crime and place that reflect any dynamic spatiotemporal variation. Through both theoretical and methodological innovation, this thesis paves a way for using new sources of data to explore variation in fear of crime in place and time as a function of the environmental context and people's routine activities within that. In doing so this chapter serves to emphasise a situational spin on fear of crime and perception of place research, achieved by exploring these concepts using crowdsourced data about people's routine activities in place and time.

1.2 Overview

This chapter served to briefly lay out the aims, contribution, and structure of this thesis. The aim of this thesis is to assess the suitability of two relatively new methodologies in criminology. These are crowdsourcing volunteered geographical information, and building a bespoke measurement tool using experience sampling method and mobile phones. I apply these to the study of peoples perceptions of, and responses to, disorder and crime.

The key contribution lies in the innovation offered by the use of these methodologies to investigate the spatial and temporal bases of active guardianship, signal disorders, and the fear of crime. I hope to contribute to the field of environmental criminology by testing of the validity and reliability of such methods. The core chapters (Chapters 4, 5, 6, 7, and 8) will serve to demonstrate some of the empirical insights these methods can produce, and consider how the use of dynamic measurement in real-world settings can open up new lines of academic enquiry, as well as be useful to criminal justice practitioners.

The next two chapters will describe the theoretical and methodological context in which the thesis situates. I emphasise how the use of new forms of data are becoming increasingly popular in a number of different social science disciplines, and their particular applicability to perception of crime and place. These phenomenon are contingently located in space and time they are a function of how people make sense of their social and physical environment as they go about their daily activities. I argue that prior work in recording both perception of signal crimes and on fear of crime has struggled to capture this dynamic, because of the reliance on surveys (that tend to go more static accounts). Yet such insight could be greatly beneficial for researchers and practitioners alike. The following chapters aim to detail and support these claims.

Chapter 2

Theoretical Background

As mentioned in Chapter 1, research presented in this thesis falls broadly within the discipline of crime science and environmental criminology. Crime science is multi-disciplinary and is concerned with the application of methodologies with the ultimate aim of reducing crime (Laycock). Environmental criminology focuses this discussion on the situational factors which contribute to the creation of opportunities for crimes to occur. The three supporting theories of crime science and environmental criminology are Routine Activity Theory (Cohen and Felson, 1979), Rational Choice Theory (Cornish and Clarke, 2008), and Crime Pattern Theory (Brantingham and Brantingham, 1981, 1993). This chapter will touch briefly on how these theoretical frameworks have contributed to the study of crime and lead to developing preventative measures for crime reduction. Their potential application to study of perception of crime is then considered.

In this chapter I argue that the above approaches can provide a framework to study events that people experience as they go about their everyday lives, based on the place-based approach of environmental criminology. Just as this approach served to innovate in the discussion of crime and place, a similar approach can do the same for the *perception* of crime and place. This framing of the study of subjective perceptions allows for new insight into fear of crime and related concepts, which can ultimately lead to preventative initiatives for reducing prevalence of such experiences. This chapter explores how such a framing of subjective perceptions fits in with the context of existing research into fear of crime, active guardianship, and signal disorders. Although fear of crime and perception of place have already been explored in great depth, I

argue that they can be further approached from a situational perspective, to provide additional insight into people's everyday behaviours. With information about micro-level fluctuation in people's routine activities, new insight can be gained into different behaviours such as active guardianship, experiences with signal disorders, and fear of crime.

Towards the end of this chapter, I propose that one reason that these subjective interpretations of crime and place have not been explored so much in crime science disciplines is due to the lack of adequate spatiotemporal data. Unlike crime data, people's subjective experiences are not currently measured in a way that has specific detail about their time and place, and therefore it is exceptionally difficult to gain an accurate understanding of their behaviour. Dynamically measuring people's subjective perceptions of their environments, as they go about their routine activities, would provide data to support a situational framing of these phenomena. The absence of such data leaves a hole to fill in this field of research. This chapter details the importance of addressing this gap and lays out the theoretical framework of collecting data about people's perceptions as they go about their everyday lives. This sets the stage for Chapter 3 to introduce a methodological framework that ultimately encourages the development of a new approach to measuring spatial and temporal variation in perception of crime and place, from which a methodology to address this gap can be formed.

2.1 Crime and its environment

All crime events take place in a specific place at a specific time. This relationship between place and criminal behaviour has been the focus of some branches of criminology research since the famous concentric rings around Chicago were discussed by Shaw and McKay (1942), who demonstrated how certain areas of the city accounted for higher crime rates, and began discussion about the possible reasons behind this. Since then, it has been repeatedly shown in various contexts that crimes concentrate in space (and in time). Sherman et al. (1989) found in Minneapolis, USA that relatively few hot spots produce most calls to police (50% of calls in 3% of places), although the mag-

nitude of concentration varies by offence type. Burglary also clusters in place and time, with repeat and near repeat victimisation having been shown for both residential and non-residential properties (Johnson et al., 2007; Johnson and Bowers, 2004; Bowers et al., 1998). Even low-level disorder seems to cluster; in their Seattle study, Weisburd et al. (2012) find that only 1.56 % of street segments account for 50% of all physical disorder. These findings of crime and disorder clustering in a place indicate that there is value in exploring the features of the environment of these places that perhaps contribute to these locations accounting for so much of the crime and disorder occurring there. Indeed, in a recent paper published in the leading journal *Criminology*, Weisburd (2015) claims that "a focus on the criminology of place provides a significant opportunity for young scholars and has great promise for advancing criminology as a science" (p.133).

The general approach of place-based criminology has been to focus on immediate situational conditions which come together in place and time to create a criminal opportunity (Wortley and Mazerolle, 2013). The main theoretical framework of environmental criminology brings together three approaches in order to study how these situational factors converge, and how they might be blocked from contributing to the creation of criminogenic opportunity. These are Routine Activity Approach (Cohen and Felson, 1979), Rational Choice theory (Cornish and Clarke, 2008), and Crime pattern Theory (Brantingham and Brantingham, 1981, 1993). Further relevant, especially regarding perception of crime and place, are ecology of crime models (Taylor et al.; Taylor, 2010; Bottoms, 2007; Sampson, 2013, 2012). Rather than giving a historical account, I will briefly summarise the innovation of each theory when approaching the study of crime, and the benefits afforded to the study of crime and place by each approach. This facilitates the argument that they might be applied to studying subjective perceptions of crime and place.

2.1.1 Rational Choice Theory

Rational choice perspective focuses on the processes behind a series of decisions the offender must make to arrive at the decision to commit the crime

(Cornish and Clarke, 2008). Cornish and Clarke (1986) personify this concept in the form of the "reasoning criminal" who, while "constrained by limits of time and ability and the availability of relevant information" (p.1), uses "the same sorts of cognitive strategies when contemplating offending as the rest of us use when making other decisions" (p.1). This rational choice has to be understood as a 'bounded rationality' which means that people make choices bounded by certain limitations. In our thinking, we must replace 'economic man' (someone who can select the optimal decision using all relevant information) with someone making choices equipped with limited knowledge and ability (Simon, 1955). This person attends a simplified model of their situation in order to make his or her choices. Simon (1955) gives the example of a seller who wants to price his products, but is limited to the knowledge he has, and will take a price that is 'good enough' without making many probability calculations to reach the most optimal price.

Kahneman (2003) explores this territory further, introducing the influence of heuristics, risky choices, and framing effects, demonstrating just some of the myriad of factors that influence decision making. An important tenet of this work on the biases that affect decision making is that these decisions are not only influenced by the factors that individuals bring with them, but also things present in the environmental context. For example, one heuristic that influences judgement is that of salience, whereby information that stands out, is novel or seems relevant is more likely to affect our thinking and actions (Dolan et al., 2010). For example, a change as simple as moving water bottles closer to the cashier in a cafeteria has been shown to increase the salience and convenience of this drink choice and thereby significantly boosting water sales (Thorndike et al., 2012). Evidently, this rational choice is something that is bounded by many factors, but ultimately has been shown to be a valid descriptive model of patterns of criminal behaviour, influencing the study of crime and leading to numerous crime prevention policies (Tilley and Farrell, 2013).

2.1.2 Crime Pattern Theory

Crime pattern theory (CPT) aims to explain the spatial and temporal patterning of crime (Brantingham and Brantingham, 1993) by focusing on how offenders and victims move around across place and time, and how these mobility patterns give rise to crime opportunities. It draws on the assertion that routine activities dictate where people regularly spend time, becoming familiar with the physical and social environment they pass through, thus building up personal activity spaces which represent their most frequent travel patterns. The visual extent of the activity space is known as their awareness space, which is essentially a collection of locations familiar to an individual (Brantingham and Brantingham, 1993). The spatial elements of these are nodes and paths. Where the nodes or paths of offenders overlap with those of targets (or the location of targets), crime opportunities can occur. Different types of crime are postulated to happen at different nodes; for example disputes between people who are acquainted are believed most likely to occur at residential nodes, whereas violent altercations between strangers are most likely at nodes where people go to drink alcohol. Nodes exhibiting high crime are likely to be part of many people's awareness spaces (Brantingham and Brantingham, 1993). These nodes are not static (Bernasco and Kooistra, 2010), but instead change with the routine activities of offenders, targets, and guardians, which is why these must also be considered to complete the theory.

2.1.3 Routine Activities Theory

Routine Activities Theory (RAT) focuses on people's everyday routine activities to identify when and where three key components needed for a crime event are likely to converge. The three elements are: a motivated offender, a suitable target, and the lack of a capable guardian. When all three elements converge, crime can occur. The concept has been visualised with the 'crime triangle' or 'problem analysis triangle'. This is formed of the inner triangle made up of the elements required for a crime event to occur (offender, place, target), and the outer triangle, which includes the possible crime prevention strategies to be employed to block the crime event from occurring (handler, manager, guardian)

(Figure 2.1). In order to develop crime prevention strategies, any one side of

Figure 2.1: Crime triangle, from Clarke and Eck (2014)



this crime triangle can be actioned upon, to block the criminal opportunity from being exploited. Approaching the study of crime from this angle has been powerful in influencing practical policies to reduce crime (Felson, 2008). RAT has made a significant contribution to the understanding of crime patterns, by shifting focus from criminal motivations to the criminal event (Felson and Cohen, 1979), with consideration of the spatial and temporal aspect of crime together.

The development of situational crime prevention, which aims to reduce crime opportunities by introducing changes to the environment (Clarke and Felson, 1993) arose from the acknowledgement of the power of the immediate context on the offender's decisions to undertake crime. These interventions emphasise the fundamental distinction between criminality, which is a longer term, multistage, complex thing, and criminal events which are the (mostly) shorter processes relating to the immediate circumstance and situation of the crime that occurs (Clarke and Felson, 1993; Clarke, 1997). Situational crime prevention can be implemented for example, by increasing surveillance in an area, using target hardening to reduce the vulnerability of the target, or using environmental management measures, to reduce the attractiveness of the target (Clarke, 1983).

There are many successful examples of SCP. One example is the reduction of both thefts of and theft from motor vehicle as a result of better security measures (Farrell et al., 2011) (removing the vulnerable target). Another, the

reduction in serious injury from alcohol-related violence after the introduction of toughened pint glasses for beer in British pubs. This meant they could no longer be used as weapons in bar brawls (Clarke and Newman, 2005; Committee et al., 2010) (removing the capable offender). Another example is how increased visibility of a property or the presence of people around it has been shown to affect burglary victimisation (Garofalo and Clark, 1992) (with occupants acting as capable guardians). Such situational crime prevention approaches offered an eventual 'what works' answer to many crime problems, helping scholars and practitioners emerge from the 'nothing works' era of criminology in the 1980s (Cullen and Gendreau, 2001). In order to be able to reach these problem-solving solutions, information needed to be gathered on the spatial and temporal aspect of crime together, to understand where people are, what they are doing, and what happens to them as a result (Clarke and Felson, 1993).

2.1.4 Ecology of crime models

Ecology of crime models focus on identifying the structural and cultural correlates and precursors of community crime levels (Taylor et al.). Their aim is to uncover what are the impacts of different features of demographic structure on current crime or changing crime? (Taylor et al.). In ecology of crime models, relevant community features could be almost anything, depending on the theory: demographic structural dimensions, land use features, reported crime rates, removal or return rates, or features of local social, cultural or political climate (Taylor, 2010). Unlike the theories described above, ecology of crime models do not limit their scope to the micro-environment. Instead they consider the interactions between macro and micro, and attempt to address these interactions in their explanations of crime (Taylor, 2010).

This approach however does also consider the effect of the environment not only on crime, but also on perception of crime. It is acknowledged within ecology of crime models that people feel safe in some locations and not in others (Bottoms, 2007). It is given that researchers therefore cannot ignore importance of spatial and social dimensions of city when studying crime and

responses to crime (Bottoms, 2007).

This importance remains significant in the face of digital innovations in communication and travel (Sampson, 2012, 2013) (as well as data production, to be discussed in great detail throughout this thesis). A great deal of research in neighbourhood concentration and the spatial inequalities of everyday life shows that neighbourhoods are not merely the settings for people's experiences, but instead are important determinants of the quantity and quality of human behaviour in their own right (Sampson, 2012). In particular with a focus on shared perceptions of disorder, Sampson (2012) argues that independent of observable visible cues (objective/ observable measures) the neighbourhood context will influence an individual's perception of disorder.

2.1.5 Crime and its environment

Evidently, the place-based approach of environmental criminology has been largely influential in theoretical and empirical developments in the study of crime. The approach has led to many crime prevention and reduction measures implemented in policy and practice, that have contributed to a reduction in various crimes. As discussed, looking to the situational factors that contribute to the creation of a crime opportunity has shifted the approach for studying crime. This shift has produced many interventions and recommendations towards 'what works' in problem solving and crime prevention. By detailing the strengths of these approaches, I hope to make the claim, that if a similar framing of *perception* of crime could yield similar results, this would lead to innovation in both research and practice.

In the next sections, I will focus on the application of the above theories to the study of fear of crime, signal disorders, and I will also detail further the crime prevention concept of guardianship, to argue that actually, it may be possible to gain further insight into these topics by exploring temporary situational fluctuation in these phenomena.

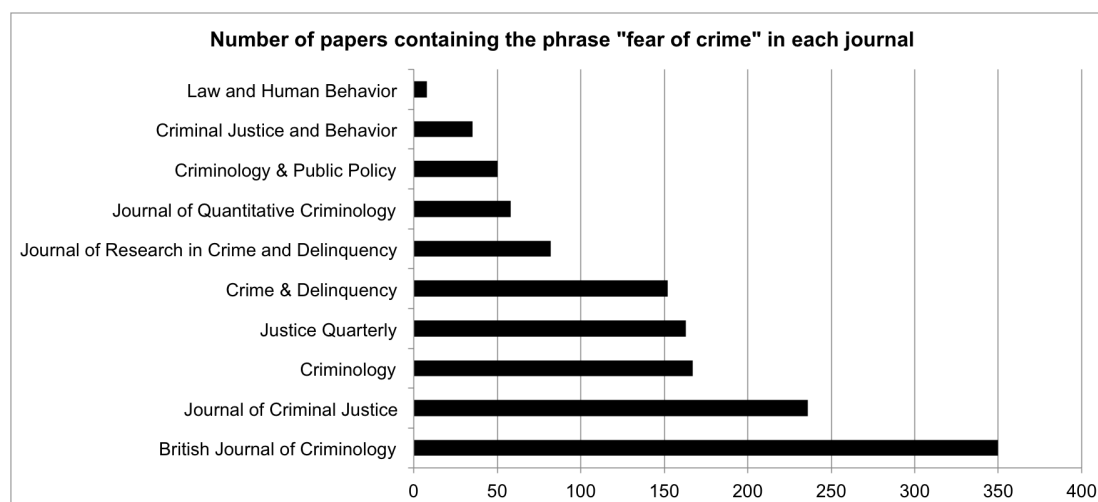
2.2 The importance of perceptions of crime

In this section, I will explore what approaches are traditionally taken to study fear of crime, and how they might not easily lend themselves to recommendations of situational prevention measures. It is possible that this is because of the nature of the approach to fear of crime that past research has taken. What follows is a presentation of a situational approach to the study of fear of crime, situated within current developments in fear of crime research and measurement.

The study of people's subjective perception of their environments in the context of crime has mainly centred around discussion of fear of crime and associated symbols such as signs of disorder. In fact, there is a long history of research into fear of crime. A search of the top 10 journals in the field of criminology¹ without any temporal filter, returns 1301 articles that contain the phrase "fear of crime". For scale, a search of these same journals returns just 982 results for the search term "organised crime", 243 for "CCTV", and 115 for "gun crime". Yet there do not exist many recommendations for situational prevention measures to reduce fear of crime.

Interestingly, looking at the distribution of papers about fear of crime within these journals highlights that there has been an emphasis on the topic in the United Kingdom especially (Figure 2.2).

¹A list of these journals was attained through using Google Scholar Metrics (www.scholar.google.co.uk) for Criminology, Criminal Law and Policing subcategory in the Social Sciences category

Figure 2.2: Fear of crime articles in top criminology journals

In fact, there is a political history of fear of crime in the UK, first appearing in the narrative of Margaret Thatcher, who referred to 'feeling safe in the streets' (Farrall et al., 2007), and present still today. How safe people feel and how much crime they perceive to be occurring has become one of London's policing priorities (London Transport Committee, 2008).

Besides being a political priority, people's perceptions of the environment in terms of safety directly impacts on their quality of life in the areas where they live and work. Security is one of the most important qualities of a residential area when determining quality of housing (Ceccato and Wilhelmsson, 2012). Fear of crime in the workplace influences operational and financial decisions made by businesses, and can lead to a variety of adverse consequences such as relocating from an area perceived as unsafe, or increasing costs that may eventually be passed on to the consumer (Casten and Payne).

Finally, fear of crime experienced while travelling is also important. Mode of travel may be influenced by perception of safety in the journey environment; higher fear of crime has been associated with less cycling and walking, and increased use of private transport modes (Mitra et al.; McDonald et al.). The walkability of an area is also affected (Kelly et al.), indeed, according to Transport for London survey results, the transport modes most affected by fear of crime are walking, travelling by bus, and cycling, with people feeling safest travelling after dark by door-to-door modes such as cars and black cabs (Transport

for London, 2011).

In fact, fear of crime can act as a complete barrier to travel (Transport for London, 2011). Therefore, to encourage the use of public transportation, the perception of safety during the entire door-to-door journey needs to be addressed (Brons and Rietveld, 2001). In this sense, fear of crime impacts not only on individual well-being, but also collective environmental health, as people are likely to be deterred from choosing more environmentally friendly transport modes, and elect to choose private, less sustainable methods to get around instead.

Although fear of crime has consequences on people's well-being in all spheres of life, research has found that it affects certain groups more than others - in the United States fear of crime on public transport has the greatest impact on those who are considered 'transport captives'. These include women, the elderly, and those with low income who are most dependent on transport and lack other means to travel (Yu and Smith, 2015). In the UK, a survey by Transport for London found that women, black and minority ethnic Londoners, disabled Londoners and gay, lesbian and bisexual Londoners are the groups most likely to be generally worried, and to have experienced worrying incidents (Transport for London, 2014a).

Evidently, no matter where (or when, or by whom) fear of crime is experienced, it has significant social, economic, and environmental impact, and therefore any means for reducing it is a priority to address through possible problem-solving approaches. This importance has become recognised by policy makers (for example, it is one of 5 objectives in the Mayor's Strategy for improving transport safety, security and reliability in London 2015-2017 (Greater London Authority, May 2015)). Yet there are not many problem-solving recommendations available for addressing fear of crime. In order for such approaches to be developed, fear of crime must first be understood as a situation-dependent experience, and its associated factors first identified, in order for them to be acted upon. However this has not yet been done, an omission that might be due to the difficulty of approaching it in a way that lends itself to such outcomes.

2.2.1 Definition(s) of fear of crime

At its most basic definition, fear of crime can be understood as a result of the presence of crime in society (Warr). However, this fear does not only appear in those who have been victimised, but also in those who have not, making fear of crime more prevalent than actual rates of victimisation (Warr). Fear of crime has been understood to mean a (negative) emotional reaction generated by crime or associated symbols (Hale), a general mistrust of others, anxiety, perceived risk, a fear of strangers, concern about deteriorating neighbourhoods (Warr), perceived risk and perceived seriousness of the consequences (Jackson and Gouseti, 2013; Warr and Stafford), and a medley of situated narratives, cultural representations, and symbolic meaning attached to environmental cues (Lupton and Tulloch). Fear of crime has been associated with a perceived lack of control over a situation (Jackson, 2013), the mixture of individual characteristics, neighbourhood structure, and citizens' perceptions (Scarborough et al.), and a result of various biases inherent systematically in different demographic groups of people with different static 'social structure' variables (Smith). These variables include age (Lagrange and Ferraro), ethnic group (Webster, 1995), and gender (Lagrange and Ferraro). From all these approaches, there derives a general consensus that fear of crime is more than a function of the risk of crime and is not always correlated to experiences of victimisation (Ceccato and Wilhelmsson, 2012).

Research into understanding what fear of crime really is extensive. Merely scanning through the 1301 papers identified in the 10 selected journals mentioned earlier by mapping the contents of their titles and abstracts highlights the diversity of approaches to date (Figure 2.3).

Figure 2.3 shows only the top 100 words of this medley of research, but the diversity of approaches is evident. Words about individual-level factors such as 'gender', 'race', 'woman', 'juvenile', as well as systemic words like 'policing', 'local', 'neighbourhood', and 'community' emerge. But words that are harder to place in the above-listed categories, like 'gun', 'violence', 'school', 'threat', and 'gang' emerge as well.

2007). The two remain interlinked and feed into one another, as signs of crime and certain situations will evoke fear of crime in the day-to-day, but also, the underlying biases and anxieties will influence how people perceive their environments, and how they interpret those situations (Farrall et al., 2007). This underlying propensity for feeling worried about crime can be understood as the 'motivated offender' (or in this case 'motivated perceiver') side of the perception of crime triangle. On the other hand, the experiential side of fear of crime corresponds to the situational approach. Applying this definition of fear of crime allows to explore further the application of environmental criminology approaches, and consider fear of crime *in situ*.

To date an environmental approach has not been so widely adopted to study more about people's *perceptions* of crime and place. Yet it can be argued that subjective interpretations of a situation can also be interpreted as a function of the environment and context. Applying environmental criminology principles to the experienced component of fear of crime model of Farrall et al. (2007), it is possible to frame fear of crime as something that people experience in certain situations, as they come across different environmental contexts during their routine activities. The next subsection explores developments in fear of crime research which support this approach further.

2.2.2 Fear of crime is situational

It has been recognised that fear of crime is transitory and situational (Fattah and Sacco, 1989), and people move in and out of shades of fear over their life courses, influenced by their experiences and by spatial, social and temporal situations (Pain). It can also be hypothesised that even over a short period of time, people will experience different levels of fear of crime, in different situations, during their routine activities. Depending on the different routine activities people are carrying out, they will come across different contexts, and interpret them in different ways, potentially encountering somewhere they might experience fear of crime.

Fear of crime has even been shown to vary with the purpose of the journey, that is whether the person was carrying out a voluntary or compulsory routine

activity (Rengifo and Bolton). Further illustrating how fear of crime is context-dependent, studies looking at gender often find that women experience higher level of fear of crime than men (Lagrange and Ferraro); however, in certain situations, it is actually men who show higher fear than women; looking specifically at public toilets, (Moore and Breeze) found that men express a more marked concern than women about assault in this specific context. In this case, even though generally women tend to be shown to have higher levels of expressive fear, the effect of this gender bias varies with the situation.

Research into within-person variation in fear of crime as a function of the salience of crime in that person's mind has also been the focus of research into psychological distance (Jackson and Gouseti, 2014; Gouseti and Jackson, 2015). This is also something which has the potential to vary within people, on a short-term scale temporally and spatially, as people may encounter something which makes crime more salient in their minds. Hence, in order to provide empirical support for variation in fear over time and place, it is not necessary to follow people as they progress through different life stages; it should be sufficient to follow them as they move through different spatial, temporal, and social contexts as people do every day, in order to observe variation in experiential fear.

As discussed in Section 2.1.4 as well, neighbourhood context also affects people's perception of place, and in turn fear of crime. The link between disorder and fear of crime is discussed in more detail in Section 2.3, however ecological models consider the effect of not only disorder, but also neighbourhood ties and patterns of interaction, informal social control, institutional resources, and routine activity patterns as well (Sampson, 2006).

2.2.3 Measuring fear of crime

The framing of fear of crime as something dynamic, rather than a static trait, as presented in the previous subsection, is actually in line with the methodological developments in the measurement of fear of crime in the past decade. These changes came about when fear of crime scholars began to question whether the generalisations of experiences with fear of crime come from the way that it

is measured, rather than how people actually feel.

The traditional approach to measuring fear of crime has been to use survey questionnaires (for examples, see Doran and Burgess (2012); Ferraro and Grange; Hale; Warr). Hence, in surveys, such as the Crime Survey for England and Wales (CSEW), (formerly British Crime Survey), variants of the question 'How afraid are you walking alone at night?' were posed to large numbers of respondents. Based on their responses ranging from very, fairly, not very to not at all, a fear of crime value is then derived to describe the population as a whole, and any differences in fear of crime reported by different subgroups are analysed (for example, see Hough). Scholars now argue that when measured this way, fear of crime becomes equated with a perceived risk based on subjective probability rather than a reflection of actual experience (Jackson, 2013), omitting many of the complexities involved with individuals experiencing fear of crime as a part of their everyday lives (Gray et al., b; Jackson and Gouseti, 2013).

For instance, measured this way, the resulting fear of crime value would not take into consideration variations in fear experience caused by perceived seriousness of crime and victimisation (Jackson, c; Warr and Stafford), sense of control over the specific event (Jackson, 2013), or any other non-static variable. Instead, this value reflects emotionally tinged 'attitudes' towards risk (Jackson, b) or future-oriented anxiety (Gray et al., d; Sacco, 2005), presenting a static picture of fear of crime, and over-representing actual rates of fear when presented as everyday experiences (Bernard et al., 1984; Farrall and Gadd, 2004b; Fattah and Sacco, 1989; Yin, 1980). Such survey questions merit answers which distort towards an 'average' experience (Hektner et al.), and respondents can be affected by a variety of social forces, such as socially desirable responding (Sutton and Farrall), which has been found to affect men more than women, and can, therefore, bias studies investigating gender differences.

Another issue with the measurement of fear of crime using retrospective, cross-sectional questionnaires is that people might revert to the use of heuristics to answer a difficult question (how worried are you about crime when you go about your day-to-day activities), potentially substituting with an easier question

(what are your thoughts about crime in general?) (Kahneman, 2011). Further, there are a number of other more dynamic personal factors to consider. For example, as mentioned earlier, psychological distance (believing one is likely to fall victim to crime when feeling proximate to a crime event spatially, temporally, or socially) dynamically affects fear of crime as experienced by individuals (Jackson, 2013; Todorov et al.; Trope and Liberman). If instead of a global summary measure, researchers were to follow fear of crime experiences of the same individuals over time, it would be possible to see within-person fluctuations. This would allow proposing that personal characteristics beyond one-dimensional groupings such as by age, gender, or ethnicity have an effect on fear of crime, and give a more dynamic image of fear of crime.

To attain a more accurate picture of fear of crime as an event experienced within a context, questions about frequency and intensity were introduced in the 2003 to 2004 sweep of the BCS (see Farrall and Gadd (2004a,b); Gray et al. (a,d)). These new measures focused on instances of 'worry', referring to concrete mental events of concern (Farrall and Gadd, 2004b) rather than the 'anxiety' of a more diffuse mental state (Gray et al., d). This movement towards measuring fear of crime as an event experienced in everyday life, rather than merely an underlying attitude or anxiety, shows a shift in focus of measurement tools, to capture this experiential element of fear of crime.

It is this approach that brings fear of crime research into the realm of situational crime prevention - if it becomes possible to identify when and where people feel worried and learn more about fear of crime as an everyday experience, it becomes more likely to find out what it is in the environment that evokes such feelings in people, and contributes to the dynamic variation of fear of crime experiences. Here 'everyday experience' is understood as something that is part of people's routine activities. This framing of fear of crime presents a picture that reveals more accurately how people 'live' it as they go about their everyday activities. This focus is closer to a situational perspective, putting fear of crime events into the context of people's everyday activities and the larger societal systems. If fear of crime is to be understood as something that people experience as they go about their everyday lives, then these fear of crime ex-

periences could be targeted by situation-specific problem-solving approaches, that can help reduce fear of crime and the associated negative consequences.

Although changes to the wording of questions described above helps to anchor people's responses to a specific instance of worry, the tool for measurement remains a cross-sectional survey (it measures the phenomenon only once, at a specific point in time, taking a static cross-section of people's experiences), and it does not get around problems associated with self-reports, including errors in recall, demand effect, or reluctance to disclose emotions (Warr). Issues with recall have always been a part of quantitative survey research in the social sciences (Loftus et al., 1992; Bernard et al., 1984). Researchers are reliant on participants to remember accurately about the subject in question, which may be prone to error. Specific to fear of crime, memories of emotional experience from longer than about two weeks prior, draw on semantic knowledge originating more from people's general beliefs related to the particular event than the specifics of the event itself (Gray et al., e; Robinson and Clore, b,a).

Another issue might emerge with demand effect. This is a type of reactivity in which individuals modify or improve an aspect of their behaviour in response to their awareness of being observed (McCarney et al., 2007). Along with the reluctance to disclose emotions, mentioned before, these known issues disproportionately affect certain groups. For example, men are more affected by desirable responding to interview questions (Sutton and Farrall). In this way, such issues introduce systematic bias into the results (Sutton and Farrall). Therefore even though such experience-based questions move closer to capturing the more expressive dimensions of public insecurities about crime (Gray et al., e), they still do not fully reflect the dynamic way in which fear of crime is experienced in everyday life.

Secondly, due to the cross-sectional nature of the questionnaire, it still does not capture the variation in fear of crime within an individual. As discussed, it is likely that these experiences vary between people with a range of factors such as time of day (day versus night), and familiarity with an area. So just as readiness to commit crime varies between people and across time and

space as the environmental backcloth to their routine activities changes (Brantingham and Brantingham, 1993), proneness to experience fear of crime might vary in a similar way. However, cross-sectional surveys take one snapshot in time of the event in question, and do not offer longitudinal insight. Therefore these new measures, while shifting emphasis towards addressing fear of crime as experienced in everyday life, still fall short of being able to capture its dynamic nature. What is meant here by 'dynamic' is that fear of crime is something that varies in a short time-frame and between micro-places (for example street segments). It is understood here to be the opposite of a static state, and instead something that changes with variation in the situational context.

In general, it is important to maintain focus on the affective reactions people have to their environments, as an understanding of the city walker's emotions might enable us to optimise physical, mental and cognitive performance and the overall quality of living (Hogertz, 2010). However, such subjective evaluation of a situation is a very dynamic element of fear of crime, which may be quite difficult to measure. One approach to measuring fear of crime as and when it is experienced is to use laboratory experiments where participants' reactions to various scenarios thought to evoke fear are recorded. For example, Fisher et al. addressed the role of the media in evoking affective fear of crime reactions by showing participants a television report of a prison escape, and measuring reactions using a state score questionnaire. Similarly, Farrall et al. (2000) used hypothetical scenario vignettes, and another questionnaire to assess affective states after being exposed to a scenario where one may potentially experience a fear of crime event.

While these studies all show an attempt to measure variation in fear of crime across various different scenarios within a person, a shortcoming that they all have in common is that they are all set in laboratories, rather than measuring real-world interactions where people experience fear of crime events live. Therefore, only predetermined causal factors of fear can be tested in such an environment, which also calls into question the extent to which these reflect genuine fear of crime experiences. In other words, their external validity cannot be made certain.

Alongside the move towards a measurement of fear of crime that is more true to everyday lived experiences, a place-based approach allows for investigation of environmental factors that correlate with fear of crime. With the growth of place-based criminology, more research has used the framework of "the criminology of everyday life" (Garland, 2001), which views the criminal event as the endpoint of a decision process (which can be conscious or subconscious), influenced by personal (for example, readiness to commit crime), and environmental (for example, suitable target and lack of capable guardian) factors (Brantingham and Brantingham, 1993). As a parallel, a fear of crime event can be experienced by someone with a certain readiness to experience fear of crime, which can depend on a number of factors which the individual brings with them (for example, age, gender, psychological distance, familiarity with an area) in the presence of certain cues in the environment (for example, disorder, graffiti).

2.2.4 Spatial resolution of fear of crime

Scholars have emphasised that people's individual perceptions of safety are situated within their understandings of the social and physical make-up of their environment (Jackson, a), pointing further to the relevance of the environmental backcloth to fear of crime. Yet unlike police-recorded crime data, fear of crime events are not recorded with a precise geotag and time stamp. Therefore fear of crime is often mapped as a generalised attribute of an aggregate area such as neighbourhoods (for example see Scarborough et al.). There are two main issues with mapping fear of crime at neighbourhood level.

Firstly, conclusions drawn from the spatial distribution of crime are affected by the level of geography used to approach them and the way in which spatial crime information is aggregated (Rengert and Lockwood). It is now more widely accepted to show spatial concentration at the micro-level (Rengert and Lockwood; Evans and Herbert, 1989; Spring and Bloc, 1988); a focus on higher geographic units such as neighbourhoods results in loss of information and inefficient focus of limited resources aimed at crime prevention (?). Further relevant here is the change in the meaning of what is being measured at dif-

ferent geographic scales. "At the individual level, fear of crime is largely the result of personal experience of crime, whilst at the neighbourhood level, fear is a function of what people experience where they live. At the macro level, fear is understood both as a social phenomenon (...) and as a generalised diffused anxiety..." (Ceccato, 2012) (p.10). Therefore, it is important to consider scale in relation to what it is that the researcher actually wants to measure. Especially when considering situational interventions, the researcher must measure fear of crime at a spatial resolution that is as small as possible, in order to identify specific situational factors that correspond with fear of crime experiences to provide problem-solving approaches.

Secondly, neighbourhood-based studies tend to attach people's fear of crime to their place of residence, restricting information to the views of the nighttime population. People spend a large proportion of their daily activities outside of their place of residence and even outside their neighbourhoods. Scholars have partially addressed this issue using questionnaires that target specific environments that people encounter, such as workplace (City of London Police and Metropolitan Police, 2009), university campus (Fisher and Nasar, 1992a; Nasar and Fisher), or various stages of public transport (Cozens et al.). However, arguably, people can experience a fear of crime event anywhere in their entire activity space, which includes home, work, and entertainment, but also various other nodes as well that are difficult to track, as well as during door-to-door travel between these places (the paths connecting the nodes). It is unrealistic to attempt to locate where people feel safe and unsafe in such a broad activity space using traditional surveying methods.

One study where researchers explored fear of crime against its environmental backdrop was carried out in Australia using retrospective cognitive mapping of areas that people avoid due to labelling them as dangerous (Doran and Burgess, 2012). The resulting maps further support the existence of micro-level geographical variation in fear of crime, showing, for example, high fear of crime along one route, and none in the surrounding areas. However, while this cognitive mapping approach illustrates a movement that values people's everyday experiences of fear of crime, it still relies on retrospective, cross-sectional

questions, retaining issues associated with these methods detailed earlier.

2.2.5 Fear of crime as a context-dependent everyday experience

The research presented in this thesis will attempt to address these omissions through offering a situational approach to complement and build upon past research, and to contribute towards a more holistic picture of fear of crime, as experienced by people in their everyday lives. To do so, a situational framework must be used to frame and define fear of crime as an event experienced in everyday life, which requires this phenomenon be accurately measured as it occurs in place and time. If this measurement were possible, then much benefit could come from identifying areas that are systematically labelled as feeling unsafe by people, whether residents or non-residents. Ability to cover people's entire activity space would reveal information about where and when people feel unsafe during the entire journey, and help identify problem areas that may benefit most from situational interventions. As outlined by CPT, offenders are likely to encounter and take advantage of crime opportunities that arise within their activity and awareness space. They are more familiar with these environments. In the case of fear of crime, the inverse can be postulated. We can consider that within the awareness space, people are more likely to feel safe, and rely more on their past experience, which for the most part will be non-victimisation, and might be more likely to experience fear of crime outside of this. Therefore we must address the perception of crime not only in the areas where people frequent, but also those they pass through less frequently, and cover all their activity space.

Further, mapping fear of crime hot spots might suggest implementing situational prevention measures that may have effects that go beyond merely increasing perceptions of safety, and increase safety from victimisation as well. For example, it is suggested that women experience more fear of crime than would be expected based on recorded crime rates because they often suffer harassment that is not reflected in reported crime statistics (Lupton and Tulloch). By identifying fear of crime event hot spots, it might also be possible to

identify hot spots of these otherwise unreported events and help reduce their occurrence. And by collecting spatial information on the environmental correlates of fear of crime, it becomes possible to look for associations with various factors and target those in problem-solving approaches to help reduce fear of crime.

In this section I emphasise the movement towards distinguishing between underlying anxieties and experienced fear events. Further, a search for environmental factors that influence fear has also been detailed. Therefore, this summary supports an approach to fear of crime as something that people experience as they go about their routine activities. Therefore, in the same way that some criminologists have moved to framing crime as something that varies with the situational context, it is possible to approach fear of crime as something that varies in place and time, within a person, with changes in the environmental context, a measurement also present in more recent developments in fear of crime research.

2.3 Signal disorders - Environmental correlates of fear of crime

Studies looking into situational factors associated with fear of crime often focus on how people evaluate their immediate environments to judge their perceived levels of safety or risk. People may rely on cues in the environment that they use to draw conclusions in their subjective evaluations of crime and place. One approach to studying the link between disorder and perception of crime and place comes from the signal crimes framework.

In order to draw inferences about their environment, people treat certain signs of disorder as 'signals'; this means they subjectively interpret the disorder as something problematic for it to evoke a negative interpretation of the area (Innes). Much research in this area has focused on the relationships between incivilities and fear in a neighbourhood (see Brown et al.; Brunton-Smith and Jackson (2012); Franzini et al.; Gau and Pratt; Hinkle and Weisburd; Jones et al.; Kohm (2013); LaGrange et al.; Roccato et al.; Scarborough et al.;

?). Such studies have repeatedly emphasised the causal effect of physical incivilities on fear of crime, showing that people consult indicators of incivility and neighbourhood disorder when assessing their safety in the environment (Kohm, 2013; Lewis and Maxfield). People use the presence of disorder as a heuristic device to provide clues about likely levels of neighbourhood crime (Wilcox et al.).

However, a major theoretical advancement of the signal crimes perspective is that the subjectivity of these signals has been emphasised. "Not everyone will tune into the same set of signals, nor will they necessarily interpret a signal in the same way" (Innes) (p.352). Drawing on the wider social scientific literature on risk perception, signal crimes makes sense of how and why different instances of disorder and crime types are rendered meaningful by people in their everyday lives (Innes).

A disorder covers any breach of prevalent norms and conventions that are disturbing or troubling. More specifically, physical disorder refers to the material detritus of anti-social behaviour and incivilities (Innes, 2014). The Home Office describes these as environmental Antisocial Behaviour (enviro-ASB) (Metropolitan Police, 2015). Enviro-ASB includes any antisocial behaviour act where the incident is not aimed at an individual or group but targets the wider environment, for example, public spaces/buildings (Metropolitan Police, 2015). Examples include litter, criminal damage, vandalism, and graffiti (Donoghue and Colover, 2011). Presence of disorder and anti-social behaviour are important influences upon how people make judgements about people and places, and the risks and threats they potentially pose. Interviews conducted by Innes (2014) reveal how people use both the visual nature of the disorder and repeated encounters with it to interpret something as a signal. Signals are the important information required to successfully negotiate a situation, and are qualitatively different from the unimportant and meaningless information, that can be effectively ignored and treated as mere background noise to the conduct of everyday life. People scan their environments, identify and interpret aspects of these that need to be attended to, and ascribe meaning to them (Innes, 2014).

Evidently, disorder in the environment interpreted as signals can have an impact on people's perception of crime. Beyond qualitative interviews however, there have not been many options to map the presence of these signals, in order to investigate their fluctuation in place and time. Collecting information from members of the community about the matters which are important to them (or the things they perceive which indicate to them problems, so signals) can also influence reassurance policing initiatives. Incorporating citizen priorities into policing practice indicates to community members that their local policing teams consider their needs (Innes, 2005). Therefore it is important to see where such disorders cluster in place and time in order to support place-based prevention measures aimed at addressing such signals.

2.3.1 Measuring signal disorders

The signal crimes perspective is based on many rich interviews, but these are difficult to replicate on large spatial and temporal scales. To date, there exist two main approaches to measuring such instances of incivilities on a larger scale: one approach measuring perceived disorder (the level of disorder people think is present in their area) (Davenport, 2010). An example of this approach can be found in the Crime Survey for England and Wales (CSEW). The corresponding question asks respondents to rate the extent to which they believe that disorder is a problem in their local area (for example see Brunton-Smith (2011) for an example of a study utilising this measure).

This measure falls victim to an issue which has been discussed in relation to the measurement of fear of crime in Section 2.2; such questions are better suited to capture overall attitudes and anxieties, as opposed to everyday experiences. Using these measures to represent people's actual encounters with disorder may overestimate the extent of the issue, as discussed in relation to fear of crime (Gray et al., b,c). As a consequence of this research, measurements of fear of crime have shifted emphasis to anchoring these questions to actual experiences (Gray et al., b). Research into *perceived* disorder on the other hand lags behind in doing the same. Therefore it is still measured by general questions where people must rate their overall attitudes towards disorder

issues, without considering the frequency and intensity of their experiences.

Also mirroring problems with measurement of fear of crime, the spatial aggregation of these questionnaire results might mask low-level variation in signal disorders. Disorder and incivilities are likely to vary *within* neighbourhoods. For example, ? found hot spots of physical disorder showed significant within-area variability; within many neighbourhoods, streets with high numbers of disorders were surrounded by streets with lower numbers. This implies that signal disorders, which when encountered can result in events of fear of crime, are not evenly dispersed in neighbourhoods either. Small geographic areas that show significantly increased rates of the measured phenomena may be rendered invisible by aggregation (Green et al.). Therefore, it is important to consider fear of crime events at the smallest possible scale in order to un-erroneously associate them spatially with elements of the environmental backcloth such as incivilities, crime, and disorder.

The second approach is to measure instances of observed disorder, usually through systematic social observation (SSO), where surveyors cover a specified area and record observed instances of incivilities (see Sampson and Raudenbush for an example of a study using this measure). While this approach reflects instances of disorder rather than general attitudes, it relies on the interpretation of the researcher rather than that of the member of the public, who is the 'motivated perceiver' to categorise something as an issue. This is a major limiting factor in terms of collecting data about signal disorders, as it is missing the identification of an instance of disorder as problematic by the perceiver, a staple of something being labelled as a signal. "The situated context in which any signifier is located, together with the characteristics of the audience members, shapes the construction of meaning" (Innes) (p.352). Essentially, in order for something to be a signal disorder, it needs to be interpreted as such (Innes et al., 2009), and simply logging all instances of observable disorder using SSO does not capture this important element. In areas where such field-work is conducted in congruence with interviews about signal disorders, a gap between observed and perceived levels of disorder is often detected (Innes, 2014).

Further, both these current modes of measurement suffer a limitation on the resolution of the spatial and temporal information that is available. Surveys ask about the general neighbourhood area and rarely make a temporal distinction between *when* a person considers the specific disorder to be an issue beyond a day versus night dichotomy. SSO is more specific in terms of geographical location but is also limited temporally in two main ways. On the one hand, it is limited to hours when the researchers are working. For example, in Sampson and Raudenbush the surveyors were on the street between 7am and 7pm, missing out on recording disorder in the environment that might occur, or be more observable, during the darkness hours for example (Davenport, 2010). The other temporal issue is that it does not account for the effect of repeated exposure to something over time. In SSO measure, one single event of litter on a pavement carries the same weight as a consistent littering issue on someone's doorstep since there is no longitudinal information to distinguish between these situations. However, residents of an area might attribute different meanings to the two. As mentioned earlier, Innes (2014) found evidence that repeated exposure is a major contributing factor to an instance of disorder being interpreted as a signal. Therefore such distinctions are important to make.

One way to address these issues could come from the concept of gathering 'community-intelligence' to support policing interventions (Innes et al., 2009). Using cognitive interview techniques and maps to gather local knowledge about signal crimes and disorders allows for the representation of not only the presence of the issue (for example instance of graffiti) but also the social reaction to it (Innes et al., 2009). Besides instances of physical disorder, work into mapping fear of crime has also focused on identifying more transient features of the environment, in order to introduce spatiotemporal variation in the environmental backcloth into the study of fear of crime. However, these techniques are resource-intensive and focus on one community area at a time.

If it were possible to attain such fine-grained information on where and when people encounter signal disorders on larger scales, this could be used to identify areas with increased opportunity for people to experience fear of crime, as these signals might serve as cues for people to attend. To facilitate this,

the research presented in this thesis will present an approach for measuring instances of people encountering signal crimes as part of their routine activities, tagged with fine-grained spatial and temporal metadata, to allow for mapping short-term fluctuation in place and time.

2.4 Active Guardianship of Place

As discussed in Section 2.1, one of the three sides of the outer crime triangle is guardianship, which is a situational measure that has been widely applied in crime prevention initiatives. From a review of over 30 years of the conceptualisation of guardianship, Hollis et al. (2013) conclude that "guardianship can be defined as the presence of a human element which acts whether intentionally or not to deter the would-be offender from committing a crime against an available target" (p. 76). For example, single parent households show higher risk for burglary even when controlling for other factors such as neighbourhood characteristics (Smith and Jarjoura, 1989), indicating that if there is someone to stay home during daytime hours and act as a guardian, the crime risk can be reduced. In fact, in a review of guardianship literature, (Hollis-Peel et al., 2011) find that every study interrogating this relationship found a preventative effect of guardianship on burglary rates.

Evidently, guardianship is a spatiotemporally specific supervision of people or property by other people which may prevent criminal violations from occurring (Felson and Cohen, 1979). Since guardianship is one of the core elements of the crime event model, it is a key situational crime prevention strategy, and knowing when guardians are present and when they are absent could help highlight when places are vulnerable to crime opportunities arising. Therefore an accurate measure of guardianship would be of value to researchers and also to crime prevention practitioners.

2.4.1 Measuring active guardianship

Traditional approaches to measuring guardianship attempt to approximate the presence of people in an area (Hollis-Peel et al., 2011). For example, one proxy measure to estimate the level of guardianship is to use the number of owner-

occupied households as a micro-level indicator (Spergel et al., 1994; Rice and Csmith, 2002). An issue with such an approach is raised by Reynald (2009) in her work on active guardianship. She questions these owner-occupiers' availability to be active guardians, asking whether they will be present in their homes at the correct time, and, even if they are present, how capable and willing are they to act as active guardians? In her theoretical framework, Reynald (2009) offers a four-tier model of guardianship intensity, where guardians can be invisible (guardian(s) unavailable), available (guardian(s) available), capable (guardian(s) available and capable of supervision), and intervening (guardian(s) available, capable of supervision, and willing to actively intervene) (Reynald, 2009). It is the last stage that represents the most active guardianship, where these guardians have the greatest preventative effect on the exploitation of possible crime opportunities present in the environment.

Therefore, proxy measurements of population counts do not reflect this requirement to be able to intervene. To address this, Reynald (2009) proposed a better measure for active guardianship which considers the aspects of the environmental context that offer opportunities for action on the part of the guardian (Reynald, 2009). This measure builds on external signs of active guardianship that are evident in the physical environment as a proxy measure to represent the intensity of guardianship in an area, based on data collected through an action-based observational approach. This approach requires field observations of properties, noting their physical features. This observational measurement instrument allows for the measure of guardianship intensity (Reynald, 2009). While a much better measure for active guardianship, this approach is very resource-intensive and constrained to cover only the study area selected, and the hours which the researchers are prepared to spend doing the observations. It also returns a temporally static, cross-sectional measure, which does not allow for mapping fluctuation in guardianship levels for example to estimate the within-day variation of crime risk.

Yet, as mentioned, guardianship is spatiotemporally specific (Felson and Cohen, 1979) so knowing how active guardianship levels fluctuate over time can help better highlight when places have increased crime risk due to de-

creased guardianship. Therefore an existing research gap emerges from the lack of an ability to map active guardianship in a way that reflects this variation. Such data could serve to identify when active guardians might move away from an area, making it more vulnerable to crime. In her thesis, Tompson (2016) proposes that "effective guardianship is dynamic over time" (p.192), so to measure this variation would allow exploring fluctuations in associated crime risk. Currently, to describe variation in guardianship, researchers compare working population to residential population. However, this may not reflect the fluctuation in *active* guardians, rather just people merely present, representing lower tiers on the guardianship in action scale (Reynald, 2010). Evidently, while theoretically developed, there exists a gap in data to empirically represent dynamic fluctuation in active guardianship, and potential temporary increases of crime risk in certain places.

Considering active guardianship then as something that fluctuates in place and time, we see the first gap for dynamic data that might be able to represent this variation. This is an interesting gap because it would need to be filled by something which measures not only where and when people are present in the environment, but also what it is they are doing, and whether that is consistent with active guardianship behaviour. This is a similar challenge as is posed when considering the measurement of signal disorders discussed in Section 2.3. We know when and where physical signs of incivility are present, and we are also able to canvas people's generalised opinions about their environments. However we are not sure how we can identify the elements of physical disorder which will be interpreted by people as signals, nor are we sure how to tie the subjective general attitudes captured by surveys to specific encounters with the disorder in the person's activity space. Similarly, while data about the presence of people is available, identifying which of those people are willing to intervene as guardians remains a more difficult task. However, measuring fluctuations in these *active* guardians has implications for identifying areas with temporarily increased crime risk.

2.5 Gap in the literature: dynamic measurements

This chapter has served to demonstrate that while research into perceptions of crime, and especially fear of crime has been vast and thorough, there remains a gap in being able to apply an environmental criminology framework, to approach perception of crime and place as something dynamic, that varies both between and within people, as they go about their routine activities. Section 2.2 described how approaching crime from an environmental framework has resulted in greater insight into situational factors that contribute to crime opportunities. A discussion of these theories illustrates that they can be applied to *perception* or crime as well. Approaching the study of perception of crime and place from such an angle would allow identification of possible problem-solving approaches. This gap can be addressed by framing perception of crime and place in a way that reflects its dynamic nature.

Further, Section 2.3 highlighted how it is also important to measure people's experiences with signal disorders in a way that reflects their experience *and* their subjective perception. Experience with signal crimes can also be understood as something people encounter as they go about their routine activities, and a movement towards the measurement of this experience in a way to reflect this longitudinal nature is highlighted.

Finally, Section 2.4 mentioned the possibilities for dynamic data about people's experiences as they go about their routine activities to represent active guardianship of places. The short-term fluctuation of active guardianship is another factor which could be better understood with data on where and when people are actively monitoring their environments, and how they move about in place and time.

In summary, the theoretical framework for this thesis is set by applying the place-based approach of environmental criminology to the study of people's perceptions of their environments, viewing fear of crime as an event people experience as they go about their everyday lives, that fluctuates dynamically with changes with spatial, temporal, and personal factors. Further, by adopting the signal crimes perspective within this thesis I attempt to look for features of the

environmental backcloth that change dynamically not only with place and time (at a micro-level) but also with the subjective "perceiver" who is interpreting his or her surroundings to make inferences about crime and place. And finally, by mapping what it is that people do as they move across their activity spaces, and when those activities are congruent with active guardianship, it becomes possible to identify areas with temporarily increased crime risk, due to decreased guardianship.

The following chapter will present a methodological framework developed to address this lack of data. It will first introduce methods to track people's experiences and perceptions longitudinally, as well as the possibility of using crowdsourced data in order to provide insight into people's everyday experiences with crime and place. By providing a framework for collecting such data, it becomes possible to support the framing of perception of crime and place from an environmental, place-based approach.

Chapter 3

Methodological Framework

The methodological innovation of this thesis is to promote the use of crowd-sourced data to gain new insight into people's everyday experiences during their routine activities, and be able to draw conclusions about subjective perceptions of crime and place. Chapter 2 argued that methodological innovation is necessary to advance our understanding of the degree to which people's perceptions of crime and place vary as they go about their everyday lives. Chapter 3 serves to introduce the methodology of crowdsourcing and situate it in the context of research into people's experiences during their routine activities. The chapter begins with a general introduction to using new technology and new data sources in social science research in Section 3.1. Then, two main approaches to collecting data are presented. First, Section 3.2s describe the use of open crowdsourced data, with a particular focus on volunteered geographical information (VGI) for research purposes. The second approach detailed in section 3.3 presents a more structured collection of VGI initiated by researchers, carried out by applying specific longitudinal research methodologies to technology-enabled surveying tools. These two are the main methodologies that are used in the empirical chapters of this thesis (Chapters 4, 5, 6, 7, and 8), and this chapter serves to outline and situate them in the broader context of developments in research methodologies for measuring dynamic elements of everyday activities.

As discussed in the previous chapter, the traditional way to collect data about people's subjective perceptions is to use surveys, developed in order to answer research questions (for example see Doran and Burgess (2012);

Ferraro and Grange; Hale; Warr). These generally are retrospective, cross-sectional questionnaires which ask people at one point in time to recall their activities, thoughts, and behaviour relating to an outcome variable of interest. For example, in measuring fear of crime, national surveys such as the Crime Survey for England and Wales (CSEW) in the United Kingdom, or the National Crime Victimization Survey (NCVS) in the United States ask a nationally representative sample about their fear of crime, while associating these experiences with some situational variables (for example: do you worry more in day or after dark?). While such surveys have many advantages, one issue is with their retrospective nature; people have to recall their activities over a long period of time, which can lead to over-generalized answers, and potentially skewed results (Gray et al., a; Jackson and Gray). Another issue is the cross-sectional approach of such surveys; hence data is collected only once from each participant, returning a snapshot of their experiences, and missing any situational, within-person variation in the outcome being measured (Mackerron, 2011; Davenport, 2010). For these reasons, as described throughout Chapter 2, data gathered in this way do not lend themselves to exploring dynamic fluctuations in situational features of fear of crime, the experience of signal disorders, and the presence of active guardians.

The methodological framework presented in this chapter will outline a new approach that allows for the understanding of spatial and temporal fluctuation in fear of crime, perception of signal disorders, and of levels of active guardianship both between and within people and places. The methodological contribution of this thesis is to introduce the use of such data and approaches to the study of the *perception* of crime and place, in order to learn more about dynamic variation and inspire future work to take similar approaches to in the future lead to situational prevention measures.

3.1 New technologies and new data sources

"Today in western societies more people are employed collecting, handling and distributing information than in any other occupation. Millions of computers inhabit the earth, and many millions of miles of optical fibre, wire and airwaves link

people, their computers and the vast array of information handling devices together. Our society is truly an information society, our time an information age” (Mason, 1986). This was written in 1986. Since then the quantity and availability of information on all topics have only increased. The internet is used daily or almost daily by 82% of adults (41.8 million) in Great Britain in 2016, compared with 78% (39.3 million) in 2015 and 35% (16.2 million) in 2006 (Office of National Statistics, 2016). The mode of internet use has also changed; mobile devices, including smartphones are used to access the internet by 71% of adults in Great Britain. Desktop computers are down in popularity with only 40% of adults using these to access the internet in 2016 (Office of National Statistics, 2016).

An entire discipline of data-intensive computing came about as a response to the massive data streams that are now produced (Kouzes et al., 2009). Such massive data sets can be terabytes (for example, the North American electric power grid operations generate 15 terabytes of raw data per year) or petabytes (for example the social networking site Facebook (www.facebook.com) captures and stores petabytes of heterogeneous information and maintains complex networks that link users) in size. Not all fields producing data of this magnitude are capable of also processing it. For example, analysts in the intelligence community need to repeatedly filter through many terabytes of data to extract the information relevant to national security issues, which is beyond current ability to analyse (Kouzes et al., 2009). Yet when analysed properly, such data can lead to valuable insight.

Advancements in technology and data collection present opportunities for researchers of social sciences to acquire data about people’s everyday activities. There are many ways in which these advancements can be utilised, and for new technologies to come to the aid of the researcher. Often such data is openly available, and can be used by researchers to learn about people’s behaviour. These data, for example, large-scale traces of social interactions and both online and offline behaviour (Diesner, 2015), are stored by businesses, government organisations, charities, and other bodies, who use them for a myriad of purposes. For example, online retailers track not only what customers

buy, but also what they looked at prior to making a purchase, to predict what books individual customers would like to read next (McAfee et al., 2012). They use this data to optimise their marketing tailored to each specific customer (McAfee et al., 2012).

There is also discussion specifically within the field of criminology around the use of 'big data' in research. For example, Google Street View has been used to supplement systematic social observation techniques to gather contextual information about environments and neighbourhoods. Odgers et al. (2012) test whether Google Street View could be used to reliably capture the neighborhood conditions of families, and Rundle et al. (2011) discuss the feasibility of using Google Street View to audit neighborhood environments. However on the other hand, Vandeviver (2014) raise questions around whether they could be exploited by offenders and might alter existing offending patterns and habits. Crowdsourcing (to be introduced in the next section, section 3.2) can also be used to enhance the extent to which such data can be used. For example, use Google Street View images scored using a crowdsourced visual perception survey to assess correlation between appearance of safety and activity.

In regards to crowdsourced data in criminology, digital communication platforms such as micro-blogging sites like twitter (discussed further in Sections 3.2 and 3.3) present both an opportunity and a challenge for researchers interested in understanding people's attitudes and behaviours (Procter et al., 2013). It can be used to gain new insight into events such as the riots in England in 2011 (Procter et al., 2013) for example. However, there exists a variety of issues with such data as well, and caution should be used when adopting them. Housley et al. (2014) warn that while "new social media can be seen to have the potential both to re-organize and change social relations, while leaving a digital footprint that can be collected, analysed and visualized", interdisciplinary working between social, computing and computational scientists as a means of realizing the theoretical, methodological, empirical and public objectives for use of such data.

But the potential of such data is great in terms of contributing to the discussion around the theoretical themes discussed in the previous chapter. For

example, Williams et al. (2016) created a Twitter measure of broken windows using a text classification procedure that was verified by 700 human annotators in an online crowdsourcing exercise. But one thing they note is the inherent bias in this data, found over and over again in such studies, resulting from the different people's propensity to tweet about issues. This not only biases the data, but could slant services to address the issues tweeted about towards these more vocal users (Williams et al., 2016). This chapter aims to discuss such new forms of data in such a way to instead of attempt to mitigate for these biases, interpret them as part of the data, and highlight that mapping of disorder measured in this way for example, represents not true disorder, rather people's subjective interpretations of their environments. Such possibilities are what will be explored by this thesis, and discussed throughout.

Further, spatial patterns of behaviour can also be explored with such data. For example, through using data from smart ticketing systems it becomes possible to measure population flow through a transport network, in order to predict route choice and ensure smooth journey experiences for users (Wang et al., 2011). The richness and detail of these data allow for more in-depth exploration of routine activities, and to move beyond the "when" and "where", to ask the "who" and "what" questions when mapping these routine activities in place and time. Besides looking only at population flow, it becomes possible to interrogate the behaviour of these populations and make inferences about how that influences the situations at those times and places.

Through these advances, already available data, as well as an arsenal of technology-enabled data collection tools provide great opportunities for researchers and analysts to gain new insights into problems previously difficult to measure. For example, to learn about people's behaviour, and make inferences about exposure to risk by finding different patterns in people's daily routine activities. One such data is crowdsourced data which will be reviewed in detail in the following section.

3.2 Crowdsourcing: harnessing the power of the many

Crowdsourcing is a term that has gained reasonable traction in the past 10 years, since it was coined in 2006, referring to harnessing information and skills from large crowds into one collaborative project (Howe, 2006). Since crowdsourcing originated in the open source movement in software (Howe, 2008), its definitions are rooted in online contexts, generally referring to it as an online, distributed problem-solving and production model (Brabham). Some early examples of crowdsourced projects enabled by the connections between people afforded by the increase in internet access are Wikipedia (www.wikipedia.org), an encyclopedia where people write articles about topics they have knowledge on, which can be edited by others, pulling together the knowledge of many contributors to provide a reference source freely available to all. Another example is the photo-sharing website Flickr (www.flickr.com), where people upload their photographs and tag them with keywords that represent what the images are of. Then people visiting these sites can search through articles or pictures using the assigned keywords, and immediately access relevant content (Surowiecki, 2005).

What is novel about the mode of production of these projects is that it is not reliant on one person to work or collect data until they meet certain requirements expected of them, but instead anyone can participate as much or as little as they are willing to. Then, the crowd's participation adds up to a complete output (Surowiecki, 2005). This concept is known as participation inequality. In economics and social sciences, this such inequality in contributions is sometimes referred to as the Pareto principle, which states that approximately 80% of the observed effect comes from 20% of the units observed (Sanders, 1987). The concept is also observed in criminology research (Weisburd, 2015). However in participation in crowdsourced projects, this discrepancy is even greater, as participation inequality has been noted to follow a 90-9-1 rule (Stewart et al., 2010). Stewart et al. (2010) identified that on the whole, about 90% of users are 'outliers', who are people who read or observe, but do not contribute to the

project. Then there are 9% of users who contribute occasionally (contributors), and 1% of users to account for almost all the contributions (super contributors) (Stewart et al., 2010). For example, Wikipedia has only 68,000 active contributors, which is 0.2% of the 32 million unique visitors it has in the U.S. alone, and the most active 1,000 people (0.003% of its users) contribute about two-thirds of the site's edits, apparently following "a 99.8-0.2-0.003 rule" (Nielsen, 2006). However, as mentioned, it is the contribution of all these users that adds up to the complete output, which in some cases is the crowdsourced data set.

A specific subset of crowdsourcing projects encourage people to submit spatial information about their local areas and combine these into one crowdsourced, spatially explicit data about their experiences and local expertise expanded over large areas. Such data is referred to as Volunteered Geographical Information (VGI), where various forms of geodata are provided voluntarily by individuals (Goodchild, 2007). While these data are available for use by researchers (if it is open data) this data collection approach is not one-sided, it can also serve to collect data for use by the participants themselves. The outputs from such data can be used to lobby for changes in their neighbourhoods, contributing to a reversal of the traditional top-down approach to the creation and dissemination of geographic information (Goodchild, 2007). For example, an application called geo-citizen allows residents of a suburban area in Ecuador to start their own participatory spatial planning initiatives (Atzmanstorfer et al., 2014). Even in itself, without requiring authoritative intervention, VGI can be used as a tool to improve people's access to services (Parker et al.). For example, Wheelmap is a mobile platform where people voluntarily provide a traffic-light-scale rating of establishments in terms of their accessibility for wheelchair users on a publicly available map (Parker et al.), being both providers and consumers of content that helps improve people's everyday lives.

The mechanism behind the creation of such VGI is 'participatory mapping', which refers to the practice of map-making by people with local knowledge who contribute to the creation of a map to represent the topic of their expertise. People contribute their time, skill, and insight to collaboratively produce a representation of their (normally local) area. People offer up their time to collect

information that has a geographical component (Haklay, 2013). In the last few decades, community-based participatory research has been used to better understand social problems (Balazs and Morello-Frosch) and has gained respect for being both pragmatic but also aiming to highlight everyone's experiences in a space equally (Cornwall and Jewkes). In certain cases, the participatory approach explicitly challenges accepted conventions about who can legitimately create maps, using what process, and for what audience (Kitchin, 2002).

For example, citizens involved with collecting data about noise pollution in their area can use that information as evidence-base when lobbying for interventions by local authorities (Becker et al., 2013). Further, users' involvement contributes to the categorisation of places as pleasant or not by non-professionals (Becker et al., 2013). The output of crowd-sourcing can have a direct influence on the world at large. For example, Yelp, a mobile application and website that allows users to rate and review restaurants in their area, has had a significant impact on restaurant revenue and market shares (Luca, 2011), putting reviewing in the hands of all patrons, and not only professional critics. Another example of VGI created by amateur citizens providing an alternative to traditional authoritative information from mapping agencies comes from mapping activities during emergencies. During wildfires in Santa Barbara, United States, volunteer maps online (the most popular of which had accumulated over 600,000 hits) had provided essential information about the location of the fire, evacuation orders, the locations of emergency shelters, and much other useful information (Goodchild and Glennon, 2010).

Participatory methodologies not only extract information but also ask people to share local experience to achieve change. Crowdsourcing and advancements in technologies allow for larger scale participation than previously possible, resulting in larger volumes of data, that can facilitate more fine-grained analysis. The next section will explore the possibilities afforded by such crowd-sourced data for research.

3.3 Crowdsourced data for research

Researchers have been employing the methodology of crowdsourcing for data collection with great success. In a project from 2007 to 2014, over one million people participated in classifying images of galaxies (Haklay, 2015). In Germany, in 2012, scientists collaborated with 5000 people to capture over 17,000 samples of mosquito, resulting in the discovery of an invasive species with implications to public health (Haklay, 2015). And there are more examples available across many domains in academic research. This section will describe the uses of crowdsourced data in research (Subsection 3.3.1), and then focus specifically on applications to the study of crime (Subsection 3.3.2). It will then discuss how this approach could be applied to the study of perception of crime and place (Subsection 3.3.3) and conclude with a discussion of its advantages and limitations.

3.3.1 Crowdsourced data for academic research

Many open data sets can be used to make inferences about people's behaviour and routine activities. With an increased automation of data collection and analysis, algorithms can now automatically extract and illustrate large-scale patterns in human behaviour (Boyd and Crawford, 2012). Lazer et al. (2009) argue that the capacity to collect and analyse massive amounts of data has transformed research in the hard science disciplines, and has the potential to accomplish the same in the social sciences as well. As with research into the perception of crime and place, research into many other social science phenomena, for example, the study of human interactions, has relied on cross-sectional, self-report data. But new technologies offer the ability to attain new insight into relationships (Lazer et al., 2009). For example, data collected about the first two years of a child's life can help identify early indicators of autism, and analysis of group interactions through email data can help determine what interaction patterns predict highly productive groups (Lazer et al., 2009).

Technological advances have made it easier than ever to harness, organise, and scrutinise massive repositories of these digital traces; computational techniques for large-scale data analysis that once required supercomputers

now can be deployed on a desktop computer (Lewis et al., 2013). Information made available, for example through the emergence of social media has created opportunities to study social processes and cultural dynamics in entirely new ways (Manovich, 2011).

For example, social media data from the micro-blogging site twitter (www.twitter.com) provides a rich data source for researchers in various disciplines (Pak and Paroubek, 2010). Twitter provides a crowdsourced data set of people's thoughts in 140 characters or less, as well as associated information about their social network connections, the time and sometimes location of their activity, and possibly other sources of information as well (such as images or video). This data is information collected as a by-product of the main activity, which is writing the tweet. By analysing the content of these tweets, researchers are able to make inferences about not only where and when people go, but also these people's demographic information, their views, their interests, and how they all link together (Pak and Paroubek, 2010).

Twitter data is made freely available through its Application Programming Interfaces (APIs), which makes it one of the most popular open data sources for studies in social sciences (Leetaru et al., 2013). Further, there are lots of data constantly being generated; the Twitter service sees about 300 million Tweets per day (Kamath et al., 2013). However, when attempting to map dynamic spatial or temporal fluctuation using tweets, the pool of usable data is somewhat reduced. Studies of the data normally find about 1 to 2 percent of tweets geocoded (Kamath et al., 2013; Leetaru et al., 2013).

But even with that data, it is possible to map people's routine activities. For example, researchers at the Consumer Data Research Centre and University College London have been analysing georeferenced tweets in London, UK, grouping tweets based on their topics (for example about sports, or transport, or containing mostly profanities) (Lansley, 2015). They then used these classifications to look into where certain topics were over-represented, and at what times. For example, they saw that tweets about train delays map nicely onto stations and rail lines that tend to have more delays and that tweets about sports from a football stadium peaked at times when there was a football game

being played at that venue (Lansley, 2015). It is important to consider the innovation here, that open data on subjective comments people make reflects their routine activities so accurately. By following people's comments on twitter, an accurate portrait of their real-world behaviour can emerge.

This also enables the mapping of people's perceptions of their environments in more detail. The content of the messages in the Twitter data can be used to classify them by their sentiment as positive, negative or neutral which has implications for mapping perception and subjective opinions in place and time (Pak and Paroubek, 2010). And there are many other openly available data sources beyond twitter which offer such data as well.

3.3.2 Crowdsourced data for crime research

Specifically looking at crime research, openly available online data has mainly been adopted by crime studies for estimating the ambient population to aid in calculating an accurate denominator for crime rates. By estimating the number of crime opportunities present in a situation, scholars aim to propose more accurate images of crime risk. A particular focus of this area is on comparing opportunity-based versus population-based crime rates. Skogan (1976) concluded that the most meaningful crime statistics are those which are related to the number of potential opportunities for victimisation. But measuring crime opportunities can be tricky.

A recent development in this area has been to take advantage of new data sets to better approximate opportunities. One such data set can be seen in the work of Malleson and Andresen (2015a), who make use of crowdsourced data in an attempt to create more accurate estimates of the population at risk for mobile crimes such as street robbery. They use Twitter data as well and find that it represents mobile populations at higher spatial and temporal resolutions than other available data, creating better denominators for calculating crime risk (Malleson and Andresen, 2015a).

However, it is possible to gain even more detail from this data, and answer not only 'when' and 'where', but also 'what' and 'who' questions, when mapping these routine activities in place and time. Geocoded tweets can be used

to perform next-place predictions and compare with the occurrence of crimes, with the goal of aiding future research into automatic crime prediction (Wang and Gerber, 2015). These approaches advance towards making use of the wealth of available data for crime research. However they leave a gap in the exploration of the utility of such data beyond just serving to measure where and when people are, but also look into what those people are doing, what routine activities they are participating in, while they move through these areas. While the content analysis with twitter mentioned in Section 3.3.1 moves towards this approach, it can also serve to explore criminological concepts as well. For example, besides at looking at people present as merely increasing the number of opportunities by increasing the number of targets, it is possible to use the detail in the data to determine whether any of those people could serve as active guardians instead, and actually bring down the crime risk through their guardianship. Further, people's subjective evaluations of place and crime are yet to be explored using such crowdsourced data, only at local scales, as discussed in this next section.

3.3.3 Applications for perception of crime and place

On a smaller scale, participatory mapping has been applied to map people's subjective experiences with crime and place in their neighbourhoods. One approach for applying this methodology to the study of people's perceptions of their environments in terms of crime and disorder comes from Innes et al. (2009). They introduce an approach to developing a community intelligence' feed that provides an insight into the principal drivers' of insecurity for specific neighbourhoods and communities. This is achieved through face to face interviews organised around a map of the subject's neighbourhood and surrounding areas. The map is used to encourage the interviewee to plot the geographic locations of where they think any troubling incidents are located (Innes et al., 2009).

As discussed in Chapter 2, prior approaches to mapping disorder, for example using data collected via Systematic Social Observation (SSO) relied on data collected by *researchers*. These (essentially) objective observers lack the

insight and knowledge of the local community members, who can flag up issues that are important to *them*, essentially identifying them as signal disorders by introducing their subjective evaluations into the data collection method. The underlying concept of the participatory mapping methodology provides a great way to get people to report concerns in their own neighbourhood. It is possible to capture observed disorder (since people report about what they actually encounter), and also perceived disorder (since people prioritise reporting things they consider problematic issues). By looking into such an approach for collecting data, Innes et al. (2009) found it can greatly aid police interventions focused on reducing the fear of crime, as it can enable the police to focus their resources on the specific problems in particular locations that are functioning as the key drivers of neighbourhood insecurity' (Innes et al., 2009).

However this study does require a lot of resources, and to scale it up to traverse larger communities might not be feasible in the current form introduced by Innes et al. (2009) which requires in-depth interviewing of community members. Further, it does not allow people to report about anything beyond the area on the map presented to them, and also does not serve as a longitudinal tracker of the issues which people raise, therefore it does not provide information about short-term temporal fluctuation in these issues.

Obtaining openly available crowdsourced data about people's perception of crime and place could result in information on what matters to them, with spatial and temporal component, in a way that can be fed back to their safer neighbourhood or local policing teams, and address the everyday issues that they face. Further, this could be achieved without requiring dedicated resources, and in a way that supports a longitudinal measure, over people's entire activity space, and in a way that can cover large geographical regions. A platform to collect such participatory mapping of perceived/ experienced crime or anti-social behaviour could provide a forum for people to convey their own experiences, and let local authorities and other bodies (such as police or safer neighbourhood authorities) know about their needs and raise a case for lobbying or otherwise requesting support or action taken for their benefit.

3.3.4 Advantages and limitations

While there have been without doubt significant insightful studies carried out with this data (Boyd and Crawford, 2012), when presenting such approaches, it is important to evaluate both the pros and cons of its implementation. An obvious advantage of this data is its longitudinal tracking of people over large-scale both spatially and temporally, which allows social science researchers to follow people's activities and even thoughts over long periods of time, across vast scales. At the same time, these data allow for analysis of micro-level variation, due to the volume of detailed data available (Manovich, 2011). Further, in the case of open data, there is no need to ask for permissions or negotiate data access in order to use it for research (Manovich, 2011). In this sense, the great advantage of this data is that it is already out there. To collect it, all that is needed is a way to be able to interpret what this data means (for example by applying a framework for its analysis), and some skill in data scraping, wrangling and cleaning, in order to be able to transform it into a usable format for research (Boyd and Crawford, 2012).

However this also creates a limitation for such data, in that because it is already available, the researcher has no say into what gets collected, and instead must make do with what is available. There are limits as to what questions researchers can ask of a data set, and what interpretations are appropriate (Boyd and Crawford, 2012). While the core chapters exploring these data will give suggestions for addressing this, it is not possible to get around the fact that some questions might not be asked in line with best practice research methods, and some variables might not be included in the measurement at all. This control over what is measured becomes sacrificed in exchange for ease of data collection, as well as possible large range and size of the data set. Collecting similar data within the scope of a research project could involve tens or hundreds of thousands of people contributing data over entire countries and for many years, which would be very costly to facilitate using traditional research methods.

Another limitation raised by Boyd and Crawford (2012) is that although

much enthusiasm around open data comes from its availability, it is not equally accessible to all. The concern over the openness of data is mirrored by Manovich (2011), who rightly points out that some data is owned by companies, who will have the advantage to processing their own data first. However, data provided by VGI sources, within the ethos of crowdsourcing, should be freely available. As mentioned, crowdsourcing comes from the open-source movement, so provides data that people willingly put into the public domain. Although interesting large data can lie under the authority of private corporations who wish to hold it back, the focus of this thesis is to explore the use of openly available crowdsourced data for crime research.

Another advantage and one motivation for using crowdsourced data within this thesis is that it has the potential to address the many limitations discussed with traditional surveying methods. "When data are collected passively while people do what they normally do anyway, the old biases associated with sampling and questionnaires disappear" (Mayer-Schonberger and Cukier, 2013) (p.30). While this is a great benefit, it is also important to keep in mind that other biases are introduced by this data. And these biases pose its main limitations.

These other biases typically raise concerns about sampling, and ultimately the generalisability of any findings that can be drawn from such data (Malleon and Andresen, 2015a). "Self-selection is an enemy of robust and scientific generalisation, and crowdsourced consultation exercises are likely to contain inherent bias" (Longley, 2012) (p.2233). The sample of the population who contributes to such data is self-selected, giving way for people more motivated to speak about the issue. Beyond only self-selection issues, an entire body of work has explored the impacts of the digital divide (for an example see Yu (2006)), which refers to certain socioeconomic groups being overrepresented in these data (Malleon and Andresen, 2015a). Gender bias has been found, showing that men tend to participate more so in such activities than women. Further work on VGI participation has also shown a divide in participation along many socio-demographic variables. Employed people, those people between the ages of 20-50, and those with a college or university degree are most likely

contributors (Budhathoki, 2010; Haklay et al., 2010). Looking into what contextual factors influence participation in Open Street Map, Mashhadi et al. (2013) find that, socio-economic factors such as population density, dynamic population, distance from the centre and poverty all play an important role. These are important to keep in mind when reporting findings based on analysis of such data.

However, as discussed by Savage and Burrows (2007), the social sciences must embrace these new forms of data that, although messy, biased and noisy, have the potential to describe social phenomena better than well-organized small surveys or even national censuses (Malleon and Andresen, 2015a). As detailed with examples in the previous sections, even with this limitation, the inclusion of crowdsourced data which are both up-to-date and specific to the problem at hand can still provide new insight in addition to the knowledge from established sources of data collected in traditional methods (Birkin et al., 2011). All of this helps us to understand the relations between the events and the occurrences that come together in unique places and provides a framework for understanding how places change over different time periods (Longley, 2012).

3.4 Bespoke data collection using new technologies

While crowdsourced data provides an insight into people's everyday lives and their experiences, it also relies on many assumptions, and needs to be cleaned and prepared, and inferences about what the data reflects must be made and justified. These steps allow for issues to emerge around the validity and reliability of such data to reflect the outcome variable of interest to the researcher. One way to address these issues is to collect information that is needed from people directly, as is the case with bespoke surveys. This section discusses the possibility of applying longitudinal survey methods to a mobile application to collect VGI for a specific study about fear of crime. Subsection 3.4.1 details the methodologies behind this approach, with examples from research, and subsection 3.4.2 discusses some of the advantages and limitations of this

method as well.

3.4.1 Methodologies behind using new technologies for crowdsourced data collection for research

In order to address the cross-sectional issue of surveys designed to measure fear of crime, as discussed in Chapter 2, it is possible to use longitudinal methods for data collection, for example time-use surveys. Participants of such surveys note down, in specific time intervals (for example every 10 minutes, or every hour) what they are doing, who they are with, and where they are. This allows for better understanding of variation in situational factors and individuals' activities. For example, by using this method, Wikström et al. (2010) demonstrated that there were clear associations between young people's activities and their exposure to criminogenic settings and ultimately, their involvement in crime (mediated by the individual's propensity to commit crime).

A similar approach, but focused on people's emotions and perceptions rather than actions is the Experience Sampling Method (ESM). This method is popular in psychology research, as it provides an approach for gaining insight into not only what people are doing, but also their interpretations of their emotional state in that situation (Christensen et al.; Hektner et al.; Scollon et al.). Like time use surveys, ESM surveys can rely on prompts at certain pre-determined intervals, but can also capture event-related prompts; participants may be instructed to fill out the questionnaire when a particular event takes place. So people might be instructed to complete an ESM survey every 10 minutes, or instead every time they experience feeling worried about crime, or each time when they use public transport (Solymosi et al., 2015).

These measurement approaches result in much more detailed and accurate data about everyday activities than do the cross-sectional approaches, but they can be more taxing on the participant. As a consequence, they might return smaller sample sizes, and have greater attrition rates. Because of this, they are also difficult to sustain over a long period of time and hence tend to be administered over short time-frames (4 days is a traditional period of collections (for example see Wikström et al. (2010)).

Downsides to using ESM are the costs and the extra load on respondents who have to remember to carry the survey with them to complete it at the appropriate time. A solution to these limitations can be found in applying this methodology to use with the (at this time) novel technology of mobile phone applications. Mobile applications offer a convenient platform to survey people about their everyday activities as they are not an extra burden to carry around, but something that people already have (Mackerron, 2011). Further, sensors such as GPS and an internal clock allow (with permission) for the collection of data such as geographic location and time of response without having to explicitly ask the participant to record it (Mackerron, 2011). This feature helps to reduce the burden on participants when submitting their data to the project database from their mobile phone and could significantly increase the collection and collation of data for projects (Aanensen et al.).

The use of mobile applications to collect data is widely used in participatory mapping exercises where people provide VGI. The use of mobile phones to collect VGI has made it easy to collect data such as coordinates (using GPS), noise or sound levels (using inbuilt sensors) while reducing the demand on people. An example of such a tool is a mobile phone software called EpiCollect (Aanensen et al.), which records information submitted by field workers together with GPS data, and has been used to collect a variety of data. For example, it has been used to monitor the geographic distribution of a certain type of cattle tick (Madder et al.). Mobile phone apps can even make the sharing of VGI possible between those who may not otherwise use the same navigational systems, maps, or coordinates. This is the case with another app, Sapelli, which is used by indigenous communities in Congo to record instances of illegal logging, sending GPS tags to researchers (Stevens et al.).

Closer to home, an example of such an app employing ESM directly is Mappiness, which extends experience sampling to incorporate satellite (GPS) location data using an app to collect a panel data set from volunteers about their everyday happiness (Mackerron, 2011). In this way, Mackerron (2011) was able to collect a large sample of accurately geocoded responses, calculate particularly good indicators of environmental quality, and make conclusions

about momentary happiness and its environmental correlates, extending the earlier work on happiness by adding a spatial element. For example, he found higher levels of happiness reported near green spaces. The key difference from openly available crowdsourced data is that the data collected here are with a specific research question in mind, within the context of a research question. Therefore the sample size might be smaller, but the result is data which was created specifically for, and meeting the requirements of, the research questions. While the relevant information of the crowdsourced data set might often be data created as a by-product of the main activity people undertake, in the case of bespoke measurement applications, the activity is to collect this information.

By building such a mobile application to measure fear of crime, it is possible to gain a new picture of fear of crime at the micro level as something dynamic that varies with place and time alongside personal characteristics. Such applications do not widely exist yet for asking bespoke survey questionnaires from participants on such a platform, and by creating one, this gap could be filled.

3.4.2 Advantages and limitations

One approach to the collection of geographically and temporally tagged data about people's experiences with fear of crime is to apply ESM to a mobile phone application. The advantage of this would be to allow for full control of the researcher to dictate what questions can be asked, and influence what data will be collected. While a more cost-intensive approach, with much smaller sample sizes, this method ensures that all necessary variables are measured for analysis, and minimises the number of assumptions that have to be made to interpret the data (in contrast with the crowdsourced data). Further, the utilisation of sensors in the mobile phone allows for quick and easy survey completion by the participants, hopefully reducing study attrition rates (Aanensen et al.).

The instantaneous nature of the data collection, provided by the data being automatically sent to the researcher, removes the need for participants to have to return to meet with the researcher for data to be recorded and stored (Mackerron, 2011). This ensures all submitted data points are retained for analysis,

and no data is lost due to the non-returning of forms by participants. As such, this approach also provides advantages, and will be explored as an avenue to collect spatially and temporally explicit, longitudinal data on people's perception of crime and place. By building bespoke data collection tool to ask people when and where they feel safe and unsafe as they go about their routine activities in near real-time, would allow for entirely new insight into how people experience fear of crime.

3.5 Applying methodological framework to measure perception of crime and place

Through the technological and informatics related advances detailed in this chapter, open crowdsourced data, as well as an arsenal of technology-enabled data collection tools, provide great opportunities for researchers and analysts to gain new insights into problems previously difficult to measure. By exploring new data sets and adopting new technology to create measurement tools for capturing perceptions of crime and place, theoretically grounded guidelines for using such data in this field can be illustrated.

The two approaches detailed in this chapter use already available crowdsourced data (Section 3.3) and make use of new technologies to facilitate bespoke crowdsourced data collection specifically for research (Section 3.4). These both apply the methodological framework of crowdsourcing to measure people's experiences with crime and fear as they go about their routine activities, in a way that results in spatially and temporally tagged data. The first approach aims to achieve this by opportunistically harnessing information already collected, while the second relies on building a data-collection platform, and running a longitudinal ESM study using mobile phone technology.

The empirical chapters of this thesis (Chapters 4, 5, 6, 7, and 8) apply both these approaches to collect data on routine activities, which can be used to gain further insight into the concepts of active guardianship, signal disorders, and fear of crime. For each chapter, I will start by arguing why I believe the new approach to data collection suits each phenomenon, and by laying out the

assumptions that must be made. I then present analysis to determine whether I can confidently say the data represents the phenomena and then conduct some descriptive analysis to present some examples of the new insights about each concept using this new approach.

The results illustrate how new insight into the perception of crime and place can be attained through each new approach. With that, I hope to create a framework for using such data in the future and outline a new approach to the measurement of active guardianship, signal disorders, and fear of crime, that could help identify situational features, and encourage actionable problem-solving approaches to reduce the fear of crime and its harmful consequences on society.

One issue with VGI, especially when it comes to governments' acceptance of these data, surrounds questions about the quality and accuracy of citizen volunteered data, as opposed to data from authoritative sources (Johnson and Sieber, 2013). However, questions about data accuracy may be less relevant to subjective perception data. If researchers want to find out how fearful people feel, the only way to acquire this information is by asking people to reveal their thoughts, independent of the method used. In context, while VGI about crime events may raise doubts about the accuracy of these data, and may be less preferable to crime event data collected by an official body such as the police, unlike a crime event, fear of crime is an internal, experiential event, which can only be recorded by the person who experiences it.

3.6 Notes on data and unit of analysis for throughout this thesis

3.6.1 Data

Before moving on to the empirical chapters, a brief introduction to the data used throughout the thesis should be presented. As these data sources are used throughout, they will be introduced here all at once, rather than multiple times in the individual chapters.

3.6.1.1 Openly available crowdsourced data

The crowdsourced VGI data used in this thesis comes from an online problem-reporting tool called Fixmystreet (www.fixmystreet.com (hereon referred to as FMS)), run by the not-for-profit organisation mySociety, who aim to "invent and popularise digital tools that enable citizens to exert power over institutions and decision makers" (MySociety, 2016). They created FMS to enable citizens to report potholes, broken street lights, and other problems in their area as easily as possible, in order to get them fixed. Using the website, citizens are able to locate their problem on a map to provide exact coordinates, choose a category for their report, give it a title, and provide a brief description. The report is logged with the time and date of reporting, and the name of the person submitting the report (unless they choose to remain anonymous). Once the report is submitted, it is emailed to the responsible local authority immediately. As of 2010, local councils in the United Kingdom such as Bromley Borough Council in North-West London have been integrating the platform into their own website, indicating to citizens that their comments are noted and responded to by their local authority. By providing this platform, FMS facilitates the crowdsourced collection of issues which people encounter in their day-to-day activities.

While this data is available nationwide, similar sites also exist in other countries as well, beyond the United Kingdom, making this approach transferable and reproducible internationally, to acquire similar data elsewhere. For example, "Fiks Gata Mi" in Norway, "Buiten Beter" in the Netherlands, "It's Bugged Mate" in Australia, "Giv et Praj" (Kbenhavn version) in Denmark, "SeeClickFix" in the United States, "SeeClickFix en franais" in France, and "FixMyStreet New Zealand" in New Zealand (Worth, 2011). Therefore, while this thesis focuses on the case study of London, UK (discussed in next section), there is no reason why this could not be translated to anywhere else in the world that is equipped with such crowdsourced complaints data. This is one major advantage of using such data sets. They already exist and cover large areas, eliminating the need for bespoke data collection exercises that require great resources.

While these reports are available to view individually on the web page

hosted by MySociety, this does not necessarily mean that it is in a form that is readily accessible to the researcher to use. In this case, the data needed to be downloaded and compiled in such a way that it would be available for analysis. One way to acquire such data is by carrying out what is referred to as a *scrape* of the data from the web page. Web scraping refers to developing and running an application that processes the HTML of a web page to extract data for manipulation. In the case of FMS, I wrote a script using Java programming languages that would open up each report, save the relevant information, close the report and move on to the next one. This script iterated through the hundreds of thousands of reports made on FMS, compiling the data to such a format where it was easily usable for research purposes. It is important to note here that this was done with the full permission of MySociety. Using this method, I collected 5 years worth of data that included the following for each report:

- Latitude and Longitude
- Topic of report (eg: 'Graffiti' or 'Litter')
- Time and date when the report was made
- Name of person reporting (if given, 'anonymous' if not)
- Detailed description of the report

The resulting database contained 276,656 usable entries for the United Kingdom after data cleaning. Chapter 4 is devoted to a detailed description of this data, including exploring its accuracy and possible biases, before Chapters 5 and 6 examine its application to research into active guardianship and signal disorders respectively.

3.6.1.2 Bespoke data collection tool

As discussed, one theoretical contribution of this thesis is to frame fear of crime as something that is continuous and changes dynamically as people move across the whole of their activity spaces. By taking this approach, and finding

empirical data to support it, the extant literature on fear of crime can be supplemented by situational information that is currently an unknown. To achieve this, I developed a new measurement tool incorporating the longitudinal approach of the experience sampling method (ESM) with the crowdsourcing approach of volunteered geographical information. This tool is a smartphone application, the development of which will be presented in great detail in Chapter 7. This tool allows for the measurement of fear of crime in real time (or as soon as possible after the event) and the collection of empirical data to reflect the dynamic variation in this experience, illustrating its situational nature. Chapter 8 demonstrates the ability of this tool to measure within-person variation in fear of crime, and thereby demonstrate that it is not a static characteristic that people have.

3.6.1.3 Traditionally collected data

In order to be able to establish how the new approaches to measuring perception of crime and place compare with existing measures, various reference data sources were used. While most of these will be detailed in the chapters where they appear, as they are used only once, a general introduction to the Metropolitan Police Public Attitudes Survey is worth being made here, as this data set features in all the empirical chapters.

The Metropolitan Police Service (MPS) has commissioned a Public Attitudes Survey (PAS) annually since 1983 with the objective of eliciting Londoners' perceptions of policing needs, priorities and experiences (BMG Research, 2014). From April 2014, the Mayor's Office for Policing and Crime (MOPAC) took responsibility for the survey (Mayors Office for Policing and Crime, 2016). Conducted on a continuous basis, through a programme of face-to-face interviews at the homes of respondents, the PAS obtains responses from a random probability sample of residents in each of the 32 boroughs across London that are policed by the MPS. Approximately 1,067 interviews per month are carried out, equating to approximately 100 interviews per Borough per quarter (BMG Research, 2014).

The PAS has been used in crime research on topics like citizens' confidence in the police (for example see Bradford et al. (2009); Hohl et al. (2010)),

and the relationship between neighbourhood characteristics like collective efficacy and crime (for example see Sutherland et al. (2013)). The topics covered in the PAS which are relevant to this thesis include local area and community, fear of crime and local crime problems, and anti-social behaviour (Mayors Office for Policing and Crime, 2016).

3.6.2 Spatial unit of analysis

This section briefly introduces the spatial setting of the empirical work presented in this thesis. Again since all chapters use the same approach, it makes sense to introduce it once here, rather than repeatedly throughout.

3.6.2.1 Study area

The chosen area of focus for this work is London. This was chosen as the MET PAS data mentioned above extends to London only, and also because the bespoke data collection was carried out in London as well, where I was based during my PhD research. London is the capital of the United Kingdom, and is one of the largest urban zones in Europe, with an estimated population of over 8 million in 2011 (Office of National Statistics, 2012). In terms of crime rates, in accordance with national trends across England and Wales, London has been declining over the past decade (with the exception being drugs offences, which have increased by 63 percent in the same period) (Sutherland et al., 2013). However, London still sees higher rates of crime than elsewhere in the country (Sutherland et al., 2013).

Administratively, London consists of the Greater London Authority (GLA), the 32 boroughs and the City of London. Boroughs are themselves divided into 624 electoral wards, which form the basic unit of administrative geography in England. Below this, electoral wards are further subdivided into 4,766 Lower layer Super Output Areas (LSOAs) (Sutherland et al., 2013). These are the units considered neighbourhoods throughout this thesis.

3.6.2.2 Neighbourhoods

Throughout the thesis, neighbourhoods are measured in Lower Super Output Areas (LSOAs). These are geographical regions designed to be more stable over time and consistent in size than existing administrative and political bound-

aries. LSOAs comprise, on average, 600 households that are combined on the basis of spatial proximity and homogeneity of dwelling type and tenure (Sturgis et al., 2014). LSOAs have been considered to represent neighbourhoods in previous studies examining the collective efficacy of London neighbourhoods as well (for example see Sturgis et al. (2014)). There are 4054 LSOAs across London, and these are used when the unit of analysis is at neighbourhood level throughout this thesis. The spatial data for boundaries were obtained from the London Datastore website

3.6.2.3 Street segments

To illustrate micro-level spatial and temporal fluctuation in experience with signal disorders, the spatial unit of a street segment is also used, in Chapter 6. The source for data for this layer is the Ordnance Survey Open Roads data, which is a layer of the connected road network for Great Britain. It contains all classified roads (such as motorways and A and B roads) as well as officially named unclassified roads (Ordnance Survey, 2016).

Chapter 4

Understanding crowdsourced problem reporting data

This chapter examines in detail the crowdsourced data used in this thesis to demonstrate the utility of using such data in crime research. To contribute towards building a template for using similar data, this chapter describes in detail the process of collecting and preparing the data set, and the theoretical rationale behind using it for the study of crime in place. In Section 4.1 I start by describing the data, and then in Section 4.2 I assess the extent to which the temporal and geographical components of this data can be relied upon to use for research. These first two sections will, in particular, explore the capacity of this data to answer 'when' and 'where' questions, by exploring the spatial and temporal reliability of this data. Then Section 4.3 will explore 'who' and 'what' questions, by looking into who participates in this information sharing, and what information is it that they are providing. Finally a discussion of the benefits but also the limitations of these data is presented, in order to assess their viability to answer research questions.

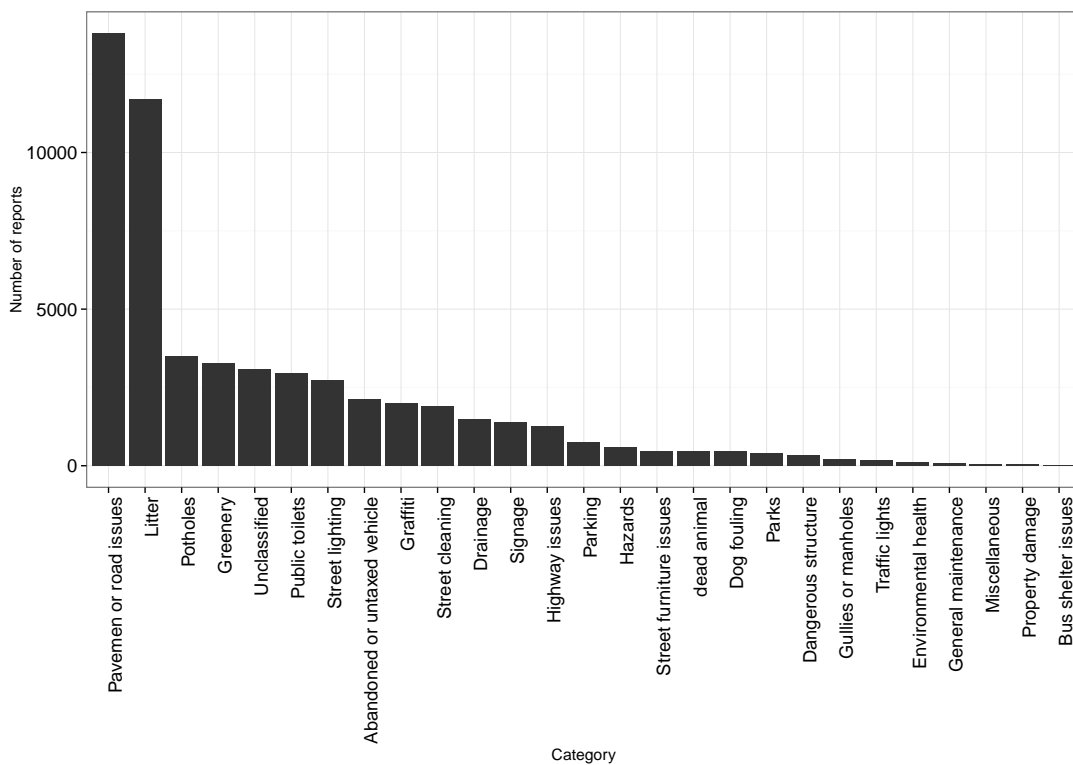
4.1 Fix My Street

As discussed in the methodological framework chapter, one source of VGI data that could be explored for research into perception of crime and place are already available crowdsourced data from online sources. The following three chapters, including this one, explore data about not only where and when people are present in an environment, but also *what* people are doing in these

places at these times, making use of the wealth of detailed information that can be harnessed with such open data sources.

As detailed in Chapter 3, the crowdsourced data in this thesis comes from fixmystreet.com and is a catalogue of almost 300,000 complaints about environmental issues that people had submitted into 236 different categories. It is possible to further subset these categories into overarching groups, which results in 27 main categories (Figure 4.1).

Figure 4.1: Overarching categories FMS reports fit into.

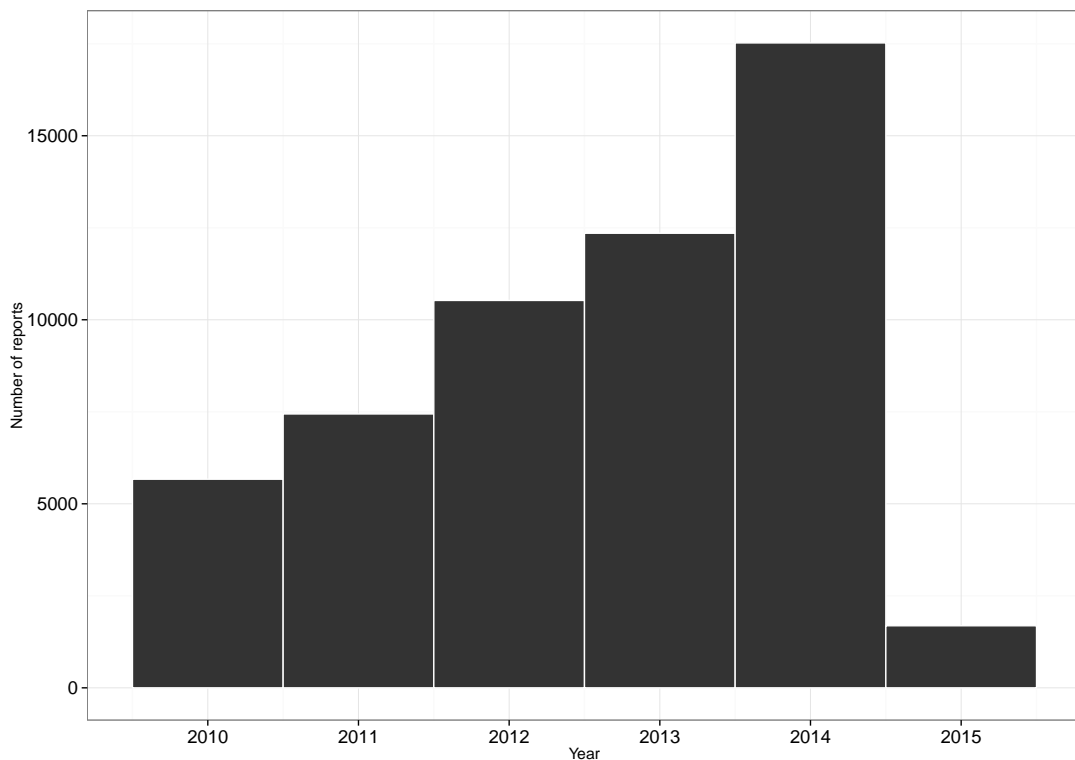


The most popular categories under which reports were submitted were 'Pavement or road issues' and 'Litter', which together contain 46% of all reports. This look at the distribution of reporting across categories gives a general idea of what people are submitting complaints about using this platform, and immediately provides some interesting insight into the environmental issues that people encounter and choose to report about most frequently.

Looking at the distribution of reports made over the past 5 years, it is possible to see that uptake of reporting has gradually increased over the years (for 2015 there is only data for January) (Figure 4.2). It appears that as time goes

on, FMS becomes more frequently used, more wide-spread.

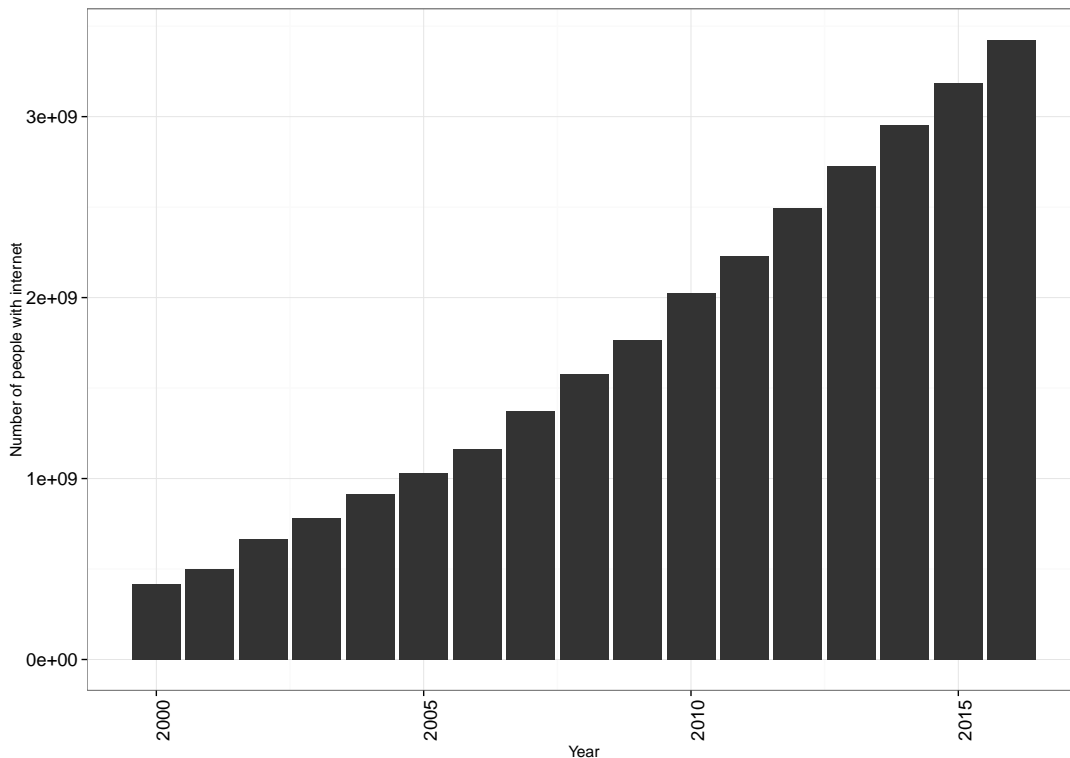
Figure 4.2: Number of reports submitted via FMS per year (2015 only up to January)



This is in line with what might be expected as there is more time for people to learn about the service, but also as more and more people have access to web-enabled devices. A graph of internet use figures (Internet Live Stats, 2016) reflects the step increase of the graph of increased FMS usage (Figure 4.3).

While the temporal pattern in reporting shows steady increase year-on-year, the spatial patterns show a non-equal distribution of reporting across London. As mentioned earlier, some London Boroughs replaced their own online street issue reporting forms with FixMyStreet software on their council website. This afforded the site a form of legitimacy, indicating to council residents that their complaints on the site are taken seriously by the council, and will be responded to in a swift and certain way. The London boroughs Barnet and Bromley incorporated FMS into their sites in 2010 and 2012 respectively, and as a result, the majority of reports that make up the dataset used in this thesis come from these two boroughs (Figure 4.4).

It is important therefore to keep in mind while using this data, that the dis-

Figure 4.3: Number of internet users per year

tribution of usage is not uniform across London. Factors such as the legitimacy provided to the platform by being incorporated into the official local authority website have an influence on the volume of reporting. Therefore in the analyses discussed in the following chapters, ways for accounting for this discrepancy in data coverage will be used, to mitigate the extent to which results are affected by this unequal distribution.

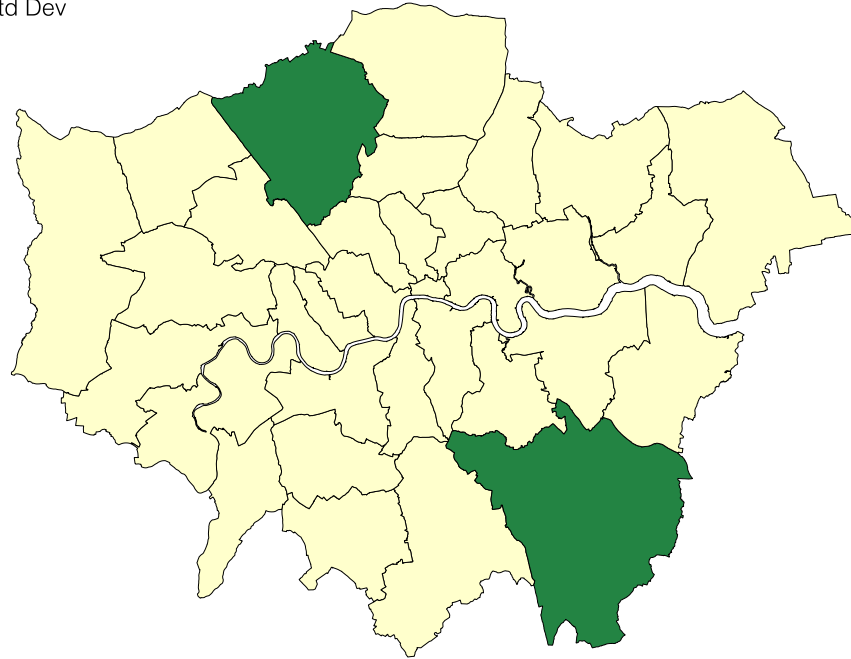
Another interesting feature of the data is the fine-grained temporal cycle which it demonstrates. Each report has with it the exact time at which the issue was reported, which can allow for a micro-level breakdown of what issues people come across at different levels of aggregation. For example, looking at within-day fluctuation of reporting is reminiscent of looking at people's daily activity patterns, demonstrating for example less reporting during night time, when most people are asleep (Figure 4.5).

While these initial insights into the spatial and temporal patterns of the data are interesting, an important note must be made and addressed before moving on to consider their implications. In considering the time and the place

Figure 4.4: Map to highlight the extent to which councils that adopt FMS are overrepresented in reports compared to all others

Distribution of FMS reports across London boroughs

□ < 0 Std Dev
■ ≥ 4.00 Std Dev



for reporting, two assumptions are made:

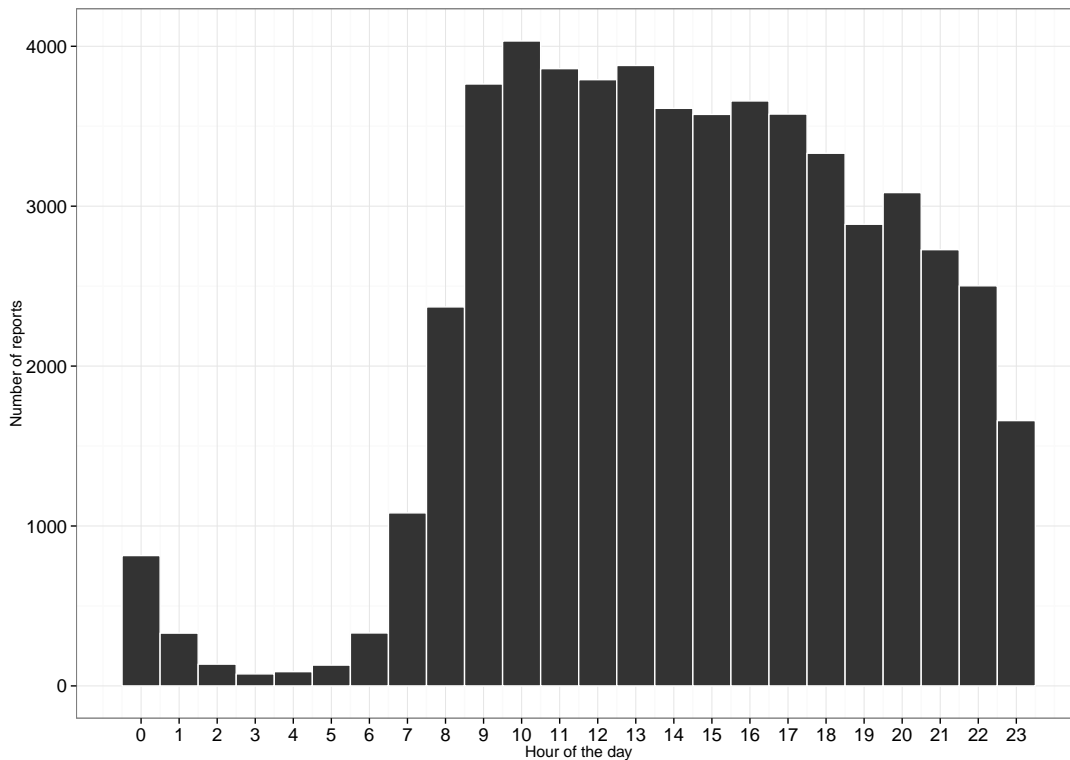
- that the location information provided with the report is the location where the person doing the reporting actually encountered the issue, and
- that the time when the report was submitted reflects approximately the time when the issue was encountered.

To address this, the following section will explore the geographical and temporal reliability of the data.

4.2 Assumptions

4.2.1 Accuracy of spatial information

FMS allows people to submit, to point level, the location of the issue they are reporting. This location needs to be accurate in order for the problem to be addressed. As discussed in the methodological framework, one distinct characteristic of VGI is that the content creators are also the consumers, and therefore have a vested interest in the accuracy of the information. Because of this,

Figure 4.5: Temporal trends in reporting reflects daily cycle in all activities

there exists a self-regulatory behaviour regarding the validity of the data, where people will strive to ensure the accuracy of the information they provide. Indeed the risk of inaccurate information provided in crowdsourced data is known in the crowdsourced literature, and it is acknowledged that these "risks are managed through self-regulation and self-management by community norms and in some cases technological architecture" (Marjanovic et al., 2012) (p.6). In the case of FMS, people might self-regulate, because, in order for the local authority to be able to address the issue being reported, it is in the content creator's interest to provide accurate locations. Further, the technological architecture is also set up to allow people to accurately provide location; a map is displayed on the site on which contributors can search known landmarks, streets, or postcodes, and they can assign a location to their incident by clicking on the map, facilitating accurate spatial information when reporting.

One way to assess whether the location provided did meet the accuracy necessary for the local council to response is provided by the FMS data itself. For local authorities who have engaged with the fixmystreet platform, it is pos-

sible to provide feedback and 'close' complaints to which they have offered a solution. While councils' involvement with participating on the site varies as a function of their motivations and capabilities to address the issues and then provide feedback about them through the FMS website, it is possible to take the example of Bromley, which has incorporated FMS into their website, hence are invested in addressing issues reported through it. According to the figures on display on the Fix My Street website, Bromley have marked 99.69 percent of their cases as fixed (excluding those labelled as "new problems" which they may not have had time to address yet). Although this percentage can drop much lower in other local authorities, it is a less plausible hypothesis that this is due to the residents of Bromley being much more skilled at locating problems on a map than residents of other boroughs. Instead it is more likely that the borough is just more responsive than others due to better resourcing or other variables.

The assertion can be made, therefore, that whilst there will be geographic inaccuracy, this will be moderated by the self-reporting process, and so it can be concluded that the spatial information in the reports is reflective of the location where people encounter the issues they report.

Another spatial issue regarding the data relates to the generation of hotspots where multiple people report the same issue. However, since the object of measurement is the perceptions of people, rather than the raw count of observed incidents, multiple reports accurately weigh the issue as more important as it affects more people encountering the issue. This is also in line with findings by Innes (2014), that indicate that repeated exposure is a significant factor in something being interpreted as a problem by citizens. Therefore I assert that trust can be placed in the spatial accuracy of this data in measuring perceptions of a problem.

4.2.2 Is the temporal information with the report a reflection of when people encounter the issues they report?

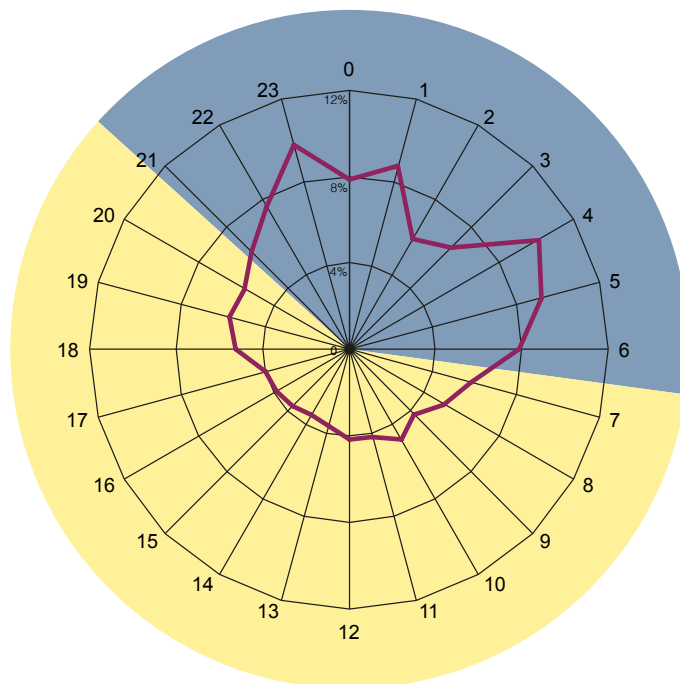
The temporal information, on the other hand, may prove to be more problematic. While FMS is also wrapped into a mobile application to enable people to

make the report *in situ* (and make it easier to provide photographs), taking time of reporting to be the time of experience with the sign of disorder is very much an assumption.

To test the viability of this assumption, consider the case of reporting broken street lights. The reasonable assumption that broken street lights will be noticed during hours of darkness rather than in daylight can be made here, because that is when the absence of light is more evident. Therefore if people report issues when they experience them, reports of broken street lights should be more prevalent during the night time, rather than day time when people notice other issues more, rather than the absence of light. Comparing the proportion of reports during daylight and night time hours (using proportion to mitigate trends in overall reporting behaviour, such as a dip in reports over night when people are at home sleeping (for illustration of this see Figure 4.5)), reveals that a higher percentage of reports are made about street lighting during hours of darkness than during daylight hours (Figure 4.6).

Figure 4.6: Percentage of all FMS reports about street lights.

Proportion of all reports that are about street lighting by hour of day



As hypothesised, people report problems with streetlights more during the

darkness, when they are also more likely to notice them, and report other issues more during the daylight hours, when they encounter those more. Indeed a chi-square test of a 2x2 table of whether the report was about street lights or anything else and whether it was made during hours of daylight or darkness¹ shows that there is a relationship between whether the report was made in hours of darkness or daylight and report being about broken streetlights ($X^2 = 389.22, df = 1, p\text{-value} < 2.2e - 16$). Indeed the table of standardised residuals further illustrates that while all other issues (not street lighting) are significantly more reported in the daytime (not dark), street lighting issues are significantly more likely reported in hours of darkness.

With this test I did not manage to falsify the claim that the temporal information with the report is a reflection of when people encounter the issues they report. Therefore it seems reasonable to maintain the assumption that the time of reporting roughly reflects the time of encounter with what is being reported.

4.3 Reporting behaviour: the Who and the What

The previous section has made the claim that this data reflects *when* and *where* people encounter problems that they deem important to report in the environment. It is also important to consider who are the people who contribute. Although FMS does not collect demographic information, it is possible to explore this using the subset of FMS data when people leave their names with the reports they make. Looking at the names reveals however, that the majority of reports are submitted anonymously. Of those who leave their name however, it is possible to look into the distribution of contributions between users.

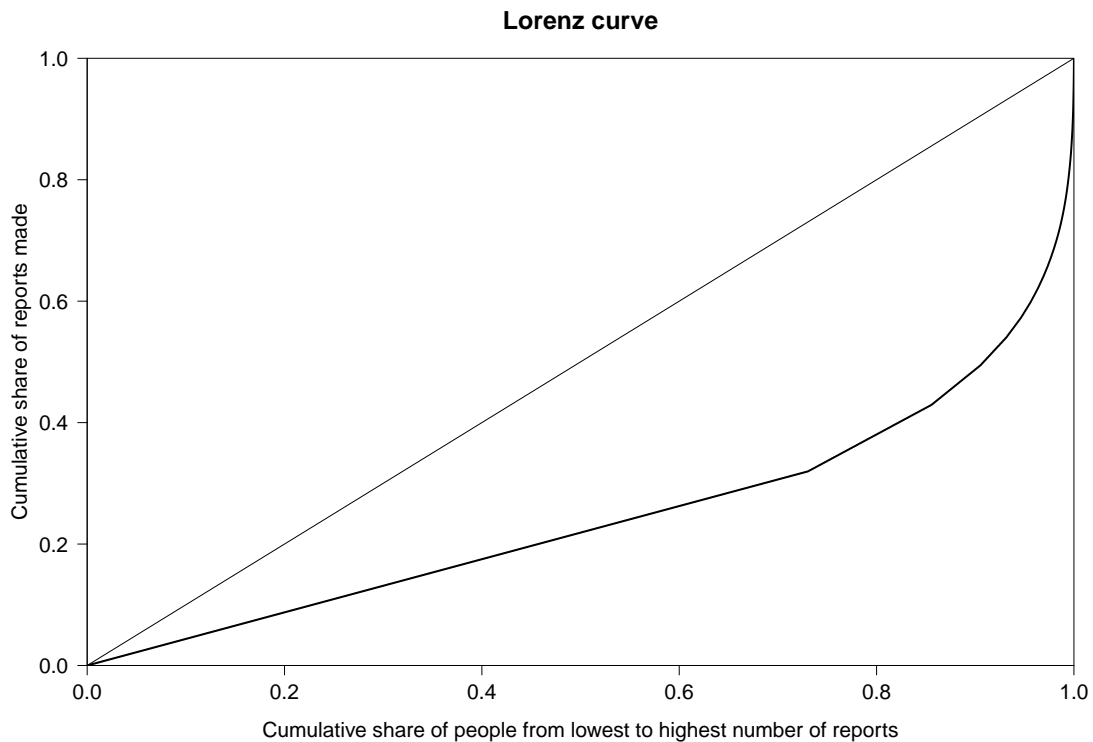
As mentioned in Chapter 3, the model for crowdsourcing is that normally it is only a few users who contribute the majority of the content, but besides these regular contributors, there is also contribution from many many people who contribute only once or twice (Surowiecki, 2005; Howe, 2008). The great benefit comes from all the contributions being recorded and compiled into one

¹To create a measure of whether the report was made during daylight hours or night time hours, data from dateandtime.com was used, and for each month, the approximate time for sunrise and sunset was used to assign each hour in that month a yes or no value to it being dark or light during that hour.

output. In this way the researcher does not lose any input from anyone, just because they choose to only participate once.

For example in this data set there was a total of 276,656 reports, of which 166,870 (60%) were submitted entirely anonymously, leaving 109,786 (40%) named reports, which were sent by only 48,065 unique individuals. If distributed equally, this would mean just over 2 reports made per person. But of course, it is not at all distributed evenly amongst these contributors. Of these, the top 10% of contributors submitted over half the reports (51%), which if this top 10 percent contributed evenly would be 12 reports per person, but of course they still do not, and the top 1% sent in one fourth of all reports, which works out to 56 reports each. The top 0.01% of contributors would make 219 reports each. On the other hand, 73% of people (who left a name) contributed only one response. In fact the median number of responses for the whole sample is 1, even though there were very people who reported over 800 issues.

It is possible to represent this inequality in distribution using a Lorenz curve, used typically to graph inequality of distribution of wealth. A perfectly equal distribution would be depicted by the straight line $y = x$ (Lorenz, 1905; Zeileis et al., 2012). Figure 4.7 shows the proportion of reports assumed by people using FMS to report.

Figure 4.7: Lorenz curve of FMS participation

The corresponding Gini coefficient of 0.51 represents the ratio of the area between the line of perfect equality and the observed Lorenz curve to the area between the line of perfect equality and the line of perfect inequality (Gastwirth, 1972). The closer the coefficient is to 1, the more unequal the distribution is (Zeileis et al., 2012).

This is interesting to note because it points immediately to the existence of 'super contributors'. As mentioned, in crowdsourcing literature, this phenomenon of 'participation inequality' has been noted, and observed to follow a more or less 90-9-1 rule (Stewart et al., 2010). Grouping people into three groups (super contributor, contributor, and outliers), Stewart et al. (2010) note that super contributors are highly motivated in their participation. In the context of FMS reports, we can understand this as a group of people who actively monitor their environments, and report any issues they come across. There is potential to consider these people as 'super guardians' of their environments, and this has implications for crime research, as guardians are a situational prevention factor, who serve to reduce crime risk by blocking criminal opportunities.

Considering the diversity of reporting by these super contributors reveals that out of the 1024 people who left 3 reports or more, only 205 reported in only one category (20%), while the majority reported in two or more of the 27 separate main categories (819 people, 80% of those who left a name with the report).

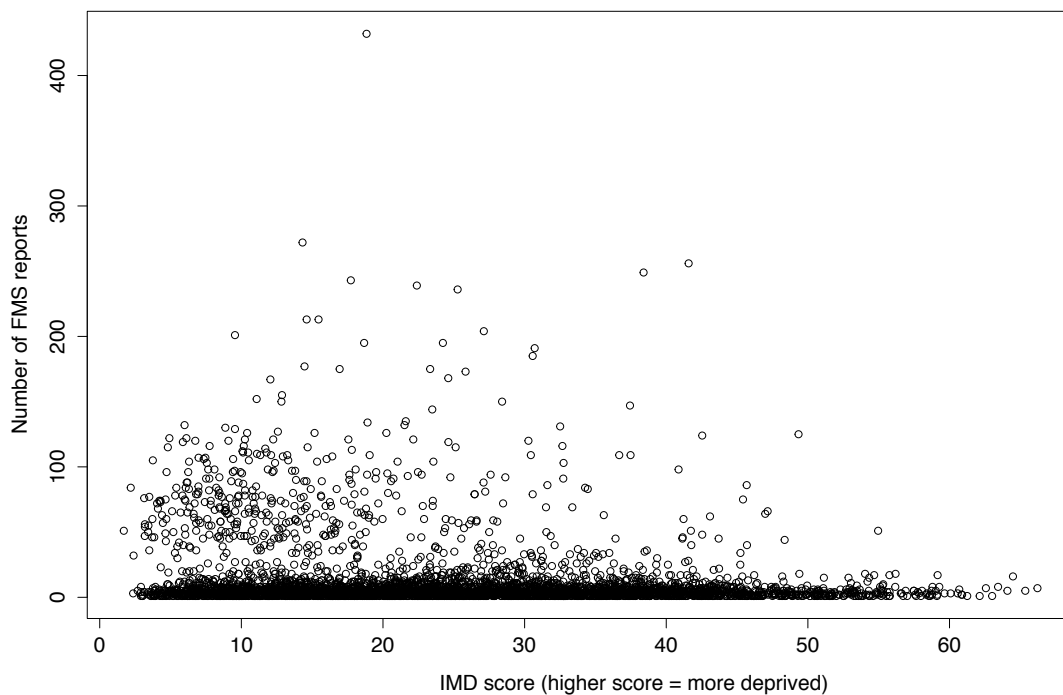
As mentioned earlier, while the reports do not collect demographic information about the person reporting, it is possible to draw conclusions based on the names left with the report. Using data from credit card and birth certificate information, Longley et al. (2015) developed a way to infer gender and age from first names, and using their database, a gender can be assigned to each report, where a name was provided. The inferential procedure is of course by no means perfect, not least because of the incompleteness of the adult population that are included in the data and the presence of young people who were not born in England and Wales (Lansley and Longley, 2016). However, such an approach is a viable means of assigning characteristics to individuals about whom only their name is known. For example, names are particularly successful as a means of estimating gender (Lansley and Longley, 2016). Therefore it will be used to explore gender differences in FMS reporting here.

For two thirds of FMS reports, no useful name for inferring gender was provided. Of these, most (over 90%) were submitted anonymously, while the other 10% were sent under obvious pseudonyms such as "concerned citizen" or "mad as hell", or providing only a first initial, from which it would be impossible to infer their gender. These reports were classed as 'unknown' in terms of gender. Men made up 24.5% of all reports, with 67,824 reports made with typically male first names, while women submitted only 8.6% of all reports, with 23,825 reports made by people with typically female first names. There are two potential reasons for this; on the one hand it is possible that men overall submit more FMS reports than women do, which would make this source of information heavily biased towards men's experiences, but it is also possible that this merely indicates that when men make reports, they are more likely to leave their full name, whereas women might more often prefer to be anonymous. However, drawing the conclusion that men leave more reports would be supported by previous research into biases in other crowdsourced data sets

(Budhathoki, 2010; Haklay et al., 2010). Such biases are important to keep in mind when interpreting results from these data.

Similarly, as mentioned in Chapter 3, increased participation also comes from wealthier areas. Using the Index of Multiple Deprivation (IMD) as a measure of poverty, Mashhadi et al. (2013) found a negative association between higher scores and level of participation. The IMD is the Government's primary measure of deprivation for small areas in England (Leeser, 2011). Using this same data confirms that the same bias is present in the FMS reporting data as well. Replicating the method of Mashhadi et al. (2013), a simple Ordinary Least Squares regression is used to consider the relationship between IMD score and coverage, measured using the number of FMS reports.

The coefficient represents the independent contribution of IMD score to coverage, the R square indicates how well the model fits the data, and the p-value indicates the significance level of the result. Results confirm that IMD score of an area has a (weak) negative correlation (*coefficient* = -0.377 , $p < 0.01$) with coverage; that is, a decrement of one unit standard deviation of poverty in a neighbourhood would improve coverage by 0.377. The R square of 0.0328 is quite low however, indicating that many other factors also play a part (for example the councils incorporating into their official reporting platforms discussed earlier). This means that more reporting comes from areas that have a lower score on the IMD, which means we hear from those 'better off' via the medium of FMS (Figure 4.8). This is a limitation that I will return to throughout this thesis.

Figure 4.8: Number of FMS reports per neighbourhood by IMD score

Evidently, FMS data, while providing a geo-tagged and time-stamped account of when and where people encounter an issue they wish to report, it is not free of the biases associated traditionally with such crowdsourced data. However, as outlined in Chapter 3, it is important to explore the potential of such new forms of data, despite its associated issues (Malleon and Andresen, 2015a), as it can help reveal new insights into how features of place can vary dynamically with time (Longley, 2012).

4.4 Discussion

Overall, FMS data has many positive implications when considered for use in research into people's everyday experiences. However it also has issues with bias in terms of the area covered (weighting towards reports in local authorities where the council has incorporated FMS into their site), and in terms of who participates (men more than women, people from wealthier areas more than those from areas with higher deprivation scores). But overall it can be assumed to represent, with a time-stamp and a geo-tag, where and when people are

reporting issues, and also what they are reporting. This is a source of data previously untapped for use in perception of crime research.

However it is important to keep in mind the limitations discussed in this chapter, surrounding this data. Its uptake is not uniformly distributed across London, with two boroughs being overrepresented in reporting activities. Further, the self-selection of who participates also introduces a bias into the data, which means that it is not representative of everyone's views and experiences, but rather of certain groups more than others'. Section 4.2 also served to discuss some of the assumptions that have to be made as well, in order to use this data to represent when and where people encounter disorder in their environments. Overall it is important to keep these limitations in mind, as they tie in to the general issues with crowdsourced data mentioned in Chapter 3, Section 3.3.4, and remain relevant to the data used here.

This chapter has served to detail the crowdsourced data used in this thesis, and to establish some of the assumptions made about the spatial and temporal elements of the data, as well as point out some of the information available to answer the *who* and *what* questions as well. FMS data can therefore be useful to explore criminological concepts by providing detailed insight into people's routine activities, and their behaviours and experiences. In the next two chapters of this thesis, I explore two possible interpretations of this data, and the rationale behind them.

Chapter 5 will now move on to the idea of 'super contributors' mentioned earlier, and argue that these people who are reporting on FMS, no matter *what* they are reporting, are acting as *active* guardians. Then Chapter 6 will use the content of these reports to investigate whether reports of issues which can be classed as disorder can represent the presence of *signal disorders*. Through exploring these topics with FMS data, the following two chapters will contribute to wider research on the topic of the exploration of crowdsourced online data for use in crime perception research.

Chapter 5

A dynamic measure for active guardianship

The previous chapter introduced crowdsourced complaints made to the website fixmystreet.com as a source of information about not only where and when people are out and about, but also what they are doing. In Chapter 3, I discussed how crowdsourced data is becoming more widely adopted in crime research, mainly to identify appropriate denominators for crime by providing accurate measures of ambient population. From such an angle, the crowdsourced data is used to learn about the 'suitable target' side of the crime triangle (see Chapter 2). However, this approach does not consider if any of these 'bodies on the street' who are potential targets could also be 'eyes on the street', or potential guardians. In this chapter I demonstrate that by using crowdsourced data about a specific activity - which is reporting problems using FMS, it becomes possible to make a distinction between the functions of these people on the street. By doing so, this chapter provides a first step in moving beyond the 'when' and the 'where' of such data to also consider the greater wealth of detail to answer 'who' and 'what' as well.

More specifically, this chapter explores the possibilities of FMS data to represent dynamic spatial and temporal fluctuation in *active* guardianship. Through using FMS data to represent active guardians, this chapter hopes to illustrate how 'bodies on the street' and 'eyes on the street' show opposite effects, which is in line with environmental criminological theory (see Chapter 2). Section 5.1 reiterates the distinction between measuring the presence of peo-

ple, and also considering what these people are doing, and their capacity to act as guardians. Then Section 5.2 proposes that crowdsourced complaints data can be used to highlight areas of temporarily increased crime risk due to drop in guardianship, distinct to areas of increased number of targets. Section 5.3 considers the relationship between baseline measures of willingness to intervene and levels of participation in FMS on a neighbourhood level. Section 5.4 then explores whether fluctuation in FMS participation can reflect fluctuation in crime risk due to temporary absence of active guardians, and how that differs from the effect of willingness to intervene as a neighbourhood attribute, and fluctuation of population count. Section 5.5 serves as a discussion for these results, and explores how these findings can help to further inform targeted prevention efforts.

5.1 Bodies on the street versus eyes on the street

Section 2.1 in Chapter 2 discussed in detail the approach of environmental criminology, and the elements necessary to converge in time and place for a crime event to occur. One of these elements is the presence of a suitable target (Felson, 2008). Much research has focused on producing appropriate measures for this suitable target, to provide accurate denominators for crime risk (for example Malleson and Andresen (2014, 2015b)). More recent innovations in this area attempt to make use of crowdsourced information to estimate on-street populations. Section 3.3 in Chapter 3 discussed these in greater detail. While these measures serve to provide more accurate denominators and result in better ways to estimate crime risk, as it varies on a micro-scale both spatially and temporally, they make the assumption that every body on the street is a suitable target.

However, depending on the level of crowding in the ambient population present, these people can also serve as guardians, rather than just targets (Grönlund, 2011). In this way, parts of this ambient population might actually belong to the guardian element of the outer crime triangle, rather than the suitable target element of the inner one. As detailed in Chapter 2, extending guardianship is a commonly used situational crime prevention approach which

aims to reduce crime opportunities by increasing the (perceived) risk of offending in an area (Guerette and Bowers, 2009). Therefore, lower levels of crime risk in an area can be predicted by increasing guardianship. This should show the opposite effect to increasing number of suitable targets, which should increase crime risk.

Building on the work of Reynald (2009), that people's willingness to act as guardians depends on their ability, their propensity, and whether individual level factors and their routine activities permit them to do so (see Chapter 2 for more detail), it can be assumed that not all individuals in that ambient population are guardians. However, it can be also assumed that some of them are. Therefore measuring the presence of active guardians in an area should show something distinct to measuring the total number of people in an area.

5.2 Measuring active guardianship using FMS

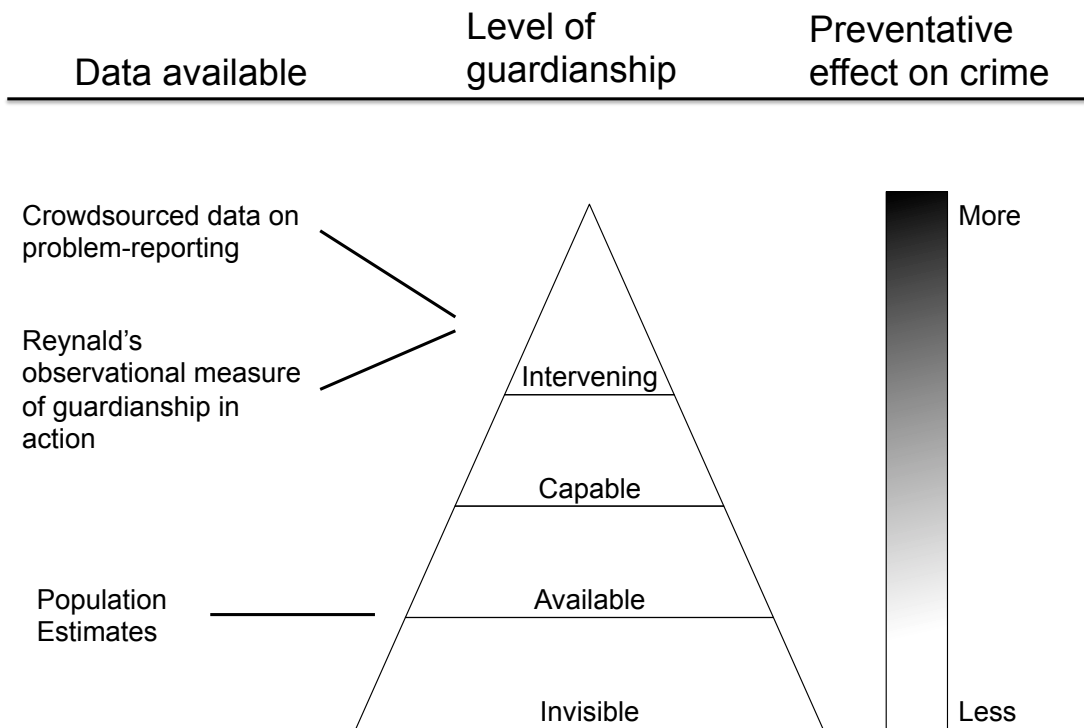
Chapter 2 detailed the great deal of innovation that has happened in recent years in the measurement of active guardianship. However measurements to date do not easily lend themselves to the mapping of micro-level dynamic fluctuation in active guardianship in a way to cover larger areas. To be able to map these intervening guardians specifically, it is possible to look to the wealth of information available in such crowdsourced data like FMS. It is possible to utilise FMS data to look into micro-level temporal fluctuations in active guardianship. Using FMS data as a proxy measure for when and where people are out and about monitoring their environments could serve as a measure for levels of active guardianship, specifically the presence of intervening guardians in neighbourhoods.

By representing active guardians with this data, micro-level temporal variation in guardianship can be identified. These areas might exhibit temporary increases in crime risk as a result of a drop in guardianship. By using FMS data to identify these areas, such temporary increases could be mapped on a large spatial scope, such as across a large city. This encourages us to attempt to map active guardianship in place and time, using data that is already available, and does not require the researcher to invest significant resources in data

collection.

Reporting an issue on FMS is a behavioural response to something that the person doing the reporting perceives to be an issue. The creation of the report requires that the concerned citizen be actively monitoring their environment around the time of reporting, near the location of the incident, and actively taking ownership over the environment. This represents a sort of digitally engaged guardianship, where people use online platforms to monitor their areas, and lobby the local authority to address the issues which these guardians find problematic. Therefore these people are making behavioural responses to the environment (reporting), and as such represent intervening guardians who are in the highest tier on Reynalds’ guardianship scale; they are available, capable of supervising, and willing to actively intervene. Figure 5.1 illustrates where this new data fits in the guardianship literature.

Figure 5.1: Data for measuring active guardianship



This crowdsourced data, whilst affected by external factors such as representativeness, discussed in detail in Chapter 4, can also serve as an open

source, readily available data set for estimating levels of active guardianship on a large spatial scale, complete also with fine-grain temporal data.

To test the claim that these data can be used to represent guardians within the ambient population, which is distinct from the number of people present who can be considered, on the whole, suitable targets, the following sections will test two hypotheses. First to determine whether FMS reporting is correlated with guardians who are willing to intervene, Section 5.3 will test whether neighbourhoods with higher levels of willingness to intervene measured with traditional survey approaches also have higher FMS reporting. After that, Section 5.4 will explore the relationship between within-day changes in levels of FMS reporting and a burglary. Burglary is chosen as it is a crime which is traditionally associated with daytime.

5.2.1 Analytical approach

Before moving on to results, a quick note about the analytical technique used in Sections 5.3 and 5.4 must be made.

The spatial unit of analysis used in this chapter is the neighbourhood level (see Chapter 3 for discussion on how neighbourhoods are defined throughout this thesis). Therefore levels of each variable are considered for each neighbourhood. As discussed in Section 3.6.2, there are approximately 600 households in each neighbourhood and overall 4054 neighbourhoods across London.

Due to the spatial nature of the data set, spatial lag regression models are used throughout. Spatial lag means that the dependent variable Y in place i is affected by the independent variables in both place i and nearby place j , which is the case in our data (Beck et al., 2006). By using a spatial lag model, the coefficient parameter reflects the spatial dependence inherent in our data, measuring the average influence of observations by their neighbouring observations. This is important because spatial autocorrelation is strong with FMS data, indicated by a Moran's I value of 0.766.

Therefore here I consider the estimation by means of maximum likelihood of a spatial regression model that includes a spatially lagged dependent variable. Unlike the traditional approach, which uses eigenvalues of the weights

matrix, this method is well suited to the estimation in situations with very large data sets (Anselin, 2004), and with over 4000 neighbourhoods, it was deemed appropriate for this dataset. Neighbouringness was calculated in GeoDa using a Queen contiguity weights construction (Anselin, 2003).

While it is tempting to focus on traditional measures, such as the R square, this is not appropriate in a spatial regression model (Anselin, 2004). The value listed in the spatial lag output is not a real R square, but a so-called pseudo-R square, which is not directly comparable with the measure given for Ordinary Least Square regression results. A better measure of fit is the Log-Likelihood, the result of a likelihood ratio test comparing the goodness of fit of two models, the Akaike information criterion (AIC), and the Schwarz criterion (SC) (Anselin, 2004). The higher the log-likelihood, the better the fit (high on the real line, so less negative is better). For the information criteria, the direction is opposite, and the lower the measure, the better the fit (Anselin, 2004).

5.3 Willingness to intervene

This section presents analysis to test with empirical evidence the theoretical assertion that FMS reporting could be used to represent active guardianship in an area. To achieve this, the first question to ask is whether higher levels of FMS reporting are associated with higher scores of willingness to intervene measured using traditional survey measure approaches. This finding should illustrate that people report more issues on FMS where they are more willing to intervene, and therefore provide support for taking this crowdsourced data to represent where active guardians are present in an environment.

People's willingness to intervene is a key factor in whether they are likely to act as active guardians or not. While people's ability to monitor their environment, as afforded by the physical design components of their neighbourhoods and residence is one factor, people's routine activities and personal inclinations are also important to consider (Reynald, 2011b). There are two main approaches to measuring willingness to intervene, one at a neighbourhood level of willingness to intervene on behalf of a common good, and one which emphasises the decision to intervene as an individual process (Reynald, 2011a).

FMS data results from people taking a behavioural response to something in the environment which the person doing the reporting interprets to be a problem (see Chapter 4). The assumption here has to be made, that these people are thereby demonstrating their individual propensity to intervene, at least through using the online platform. This section tests whether the reporting also comes from areas with high neighbourhood levels of willingness to intervene.

As mentioned in Chapter 3, the traditional measure of willingness to intervene comes from a set of survey questions from the Metropolitan Police Service Public Attitudes Survey (METPAS). Willingness to intervene is measured by the following three questions in the METPAS:

- Q3K: If any of the children or young people around here are causing trouble, local people will tell them off
- Q3J: The people who live here can be relied upon to call the police if someone is acting suspiciously
- Q3I: If I sensed trouble whilst in this area, I could get help from people who live here

These were used to create a composite score of willingness to intervene at a neighbourhood level. This same approach was used by Sutherland et al. (2013) to explore the relationship between collective efficacy (of which willingness to intervene is one element) and violence in London. All responses were coded to a number from 1 to 5, with an answer of 'Strongly agree' being 5 and 'Strongly disagree' being 1. Aggregate scores for each neighbourhood were calculated by taking the mean of the responses from residents within each neighbourhood, in line with Likert scale questionnaire analysis best practice (Clason and Dormody, 1994; Boone and Boone, 2012; Johns, 2010). This score is then compared with the level of contribution to the crowdsourced data about environmental problems from each neighbourhood, measured by the total volume of FMS reporting.

The first research question set out to answer whether increased reporting takes place in areas with higher willingness to intervene. So to assess the

relationship between the composite willingness to intervene score, and the volume of FMS reporting in each neighbourhood, a spatial lag regression model is used. The Likelihood Ratio Test which is the diagnostic test for spatial regression returns a value of 90.36 which is significant at $p = 0.001$. This means, comparing with the null model (classic OLS regression), results confirm the strong significance of the spatial autoregressive coefficient (Anselin, 2004).

The coefficient for number of FMS reports is positive, indicating a positive relationship between the number of FMS reports in a neighbourhood and a higher composite score on willingness to intervene (coefficient: 0.006, p -value = 0.03). This means that more reporting activity comes from neighbourhoods where residents rate each other as more likely to intervene in the case that something is out of the ordinary (see METPAS questions above). The regression output shows a weak fit, with an R square value of 0.028.

It should be acknowledged here that there are likely to be a variety of factors which will influence perceived willingness to intervene in a neighbourhood, and also levels of FMS reporting, leading to the low R square value, but nevertheless, this finding provides empirical support for a link between FMS reporting and willingness to intervene. Neighbourhoods where there are more people out and about monitoring the area, as measured by the crowdsourced FMS data, show higher levels of willingness to intervene, something that is a component of active guardianship. In these areas, provided that they have the situational capacity, residents have a greater chance to intervene, and act as active capable guardians.

However the weak result means that there are a few issues to be pointed out here. These prevent raw count of FMS reports being taken as a proxy for active guardianship. As mentioned when discussing the bias in the uptake of reporting discussed in Chapter 4, Section 4.1, there are too many other factors that influence volume of reporting, other than just the number of active guardians in an area. Another issue is that there are potentially many active guardians who are present but use other means of intervening, not FMS reports. However, FMS does capture some guardianship, and this can still be useful for research. Therefore, one way to use this measure, is to look at the

movement of the active guardians who *are* captured with this measurement. To be able to do this, it is possible to look at fluctuation in the activity of these active guardians. More specifically, we can look at within-day changes in their guardianship levels. The next section will therefore use FMS in this way, to produce a measure of within-day changes in active guardianship, measured using crowdsourced data.

5.4 Fluctuation in crime risk

As discussed in Section 5.1, fluctuation in crime risk, measured using crowdsourced data to map the movement of potentially suitable targets has been successfully applied. However, Section 5.3 demonstrated that crowdsourced data also has the potential to capture some active guardians, who, moving about in their environments, also potentially influence fluctuations in crime risk. This section examines the effect of these active guardians on burglary rates.

Burglary is a crime which has shown within-day temporal fluctuation; unoccupied residences in daytime tend to be the most popular targets (DAlessio et al., 2012). While ambient population do not necessarily provide suitable targets for burglary, since the targets are buildings rather than the individuals, it is possible to make a link between increased number of people in the area and burglary, using crime pattern theory (Brantingham and Brantingham, 1995). From a spatial perspective, research has shown that places that are busier tend to suffer from higher crime rates. This has been shown to be true for burglary (e.g. (Beavon et al., 1994; Johnson and Bowers, 2010; Davies and Johnson, 2015)). A candidate explanation for this is that these places are in multiple offenders' awareness spaces and hence are locations where they collectively meet opportunities. More recently consideration has been given to the temporal element of awareness spaces; offenders can only commit (physical) crime in areas when they are there (e.g. (Bowers and Johnson, 2015)). Hence an increase in ambient population might indicate the presence of more offenders and more opportunities to offend in certain areas at certain times. It is therefore prudent to look for variables that can more accurately chart the temporal locations of active crime preventers to track changes in guardianship

in greater isolation from the movements of the general population.

To test the hypothesis that higher levels of active guardianship measured using the available data will be associated with lower levels of crime, it is important to first look at how guardianship and crime levels are associated. To create a baseline, the willingness to intervene score for each neighbourhood is considered as a static feature of the environment, calculated from the MET PAS survey, as seen above. In line with active guardianship theory, neighbourhoods where people are more likely to intervene as a baseline generally should have lower rates of burglaries. Indeed, a spatial lag model shows that there is a negative relationship between a higher score on willingness to intervene and burglary rate (per 100 properties) in a neighbourhood (Table 5.1).

But as argued earlier in this paper, such static measures show only a baseline level of guardianship and are not able to reflect temporal variation in guardianship. As such, this data would not be able to highlight areas with temporarily increased crime vulnerability as a result of the movement of active guardians in place and time. This is a key feature of the guardianship element of routine activity theory that is as yet unmeasured. To attempt to reflect this temporal variation, one plan would be to look at willingness to intervene and the general population change between nighttime and daytime together. This model would incorporate overall population change, as well as the baseline willingness to intervene, so the two traditional measures.

To do so, a measure of population change during the daytime is calculated, to identify areas with potential temporary increases in risk during the daytime. To calculate this measure, the total nighttime population is subtracted from the total daytime population in each LSOA (both available from the 2011 UK population census), to give a daytime population change score. Therefore a positive score means that there are more people in the area in the daytime, and a negative score means that people move away in the daytime, possibly leaving the neighbourhoods more vulnerable to crime due to an absence of guardians, who measured by census data, represent guardians at the lowest tier in Reynald's guardianship model.

This measure is then added to the model to see whether baseline willing-

ness to intervene (static active guardianship), together with a change in daytime guardianship (compared with nighttime guardianship) has a preventative effect on burglary. The log likelihood score of this model has a higher value (moved closer to zero from previous models) indicating a better fit model, however results show that actually this population change measure shows a positive relationship with burglary rate, so essentially when there are more people in the area, there is higher burglary rate (Table 5.2). This is consistent with the reasoning above, that more ambient population in an area can result in higher burglary rates. However, it also indicates that population change in this way does not represent the presence of *active* guardians, who reduce crime risk by actively monitoring their environments.

Instead, the change in FMS reporting is hypothesised to represent the movement of these active guardians between day and nighttime. The people monitoring their environment, and participating in FMS represent a layer of active guardians who sit in tier 4 in Reynald's model. Creating a measure of when people move away in the daytime compared to nighttime, as described above, should give an indication of areas with decreased daytime active guardianship. To assess whether this is the case, the active guardianship measure is finally introduced into the model.

As before, the difference in daytime and nighttime reporting is used as a measure (rather than just the count of FMS reporting in day and in night-times), to mitigate an issue mentioned earlier with unequal coverage of areas by FMS reporting overall. Subtracting FMS reporting in the daytime from the nighttime should identify neighbourhoods with temporary increase in vulnerability to crime due to the short-term absence of the capable guardians, who are at other times present in the area, as captured by this data in the nighttime reporting numbers. By incorporating this measure, it is now possible to model the burglary rate as predicted by baseline willingness to intervene measure, by difference in daytime and nighttime populations and also difference in daytime and nighttime active guardianship as captured by FMS data (Table 5.3).

Table 5.1: Model 1: Willingness to intervene in neighbourhood vs burglary rate

Variable	Coefficient	Probability	Log likelihood	AIC	SC
Willingness to intervene	-0.068	0.001	-5825.86	11657.7	11676.6

Table 5.2: Model 2: Willingness to intervene and daytime population change in neighbourhood vs burglary rate

Variable	Coefficient	Probability	Log likelihood	AIC	SC
Willingness to intervene	-0.058	0.006	-5815.93	11641.9	11673.4
Daytime population change	0.00003	0.00001			

Table 5.3: Model 3: Willingness to intervene and daytime population change and active guardianship change in neighbourhood vs burglary rate

Variable	Coefficient	Probability	Log likelihood	AIC	SC
Willingness to intervene	-0.059	0.006	-5814.1	11638.2	11669.7
Daytime population change	0.00003	0.00001			
Daytime active guardianship change	-0.004	0.055			

Table 5.4: Model 4: Willingness to intervene and active guardianship change in neighbourhood vs burglary rate

Variable	Coefficient	Probability	Log likelihood	AIC	SC
Willingness to intervene	-0.068	0.001	-5823.98	11656	11681.2
Daytime active guardianship change	-0.004	0.053			

The log likelihood score of the model has a higher value (moved closer to zero from previous models) indicating a better fit model. Similarly, both AIC and SC values drop, indicating a better fit as well. This is important to note, as when fitting models, it is possible to increase the likelihood by adding parameters, but doing so may result in overfitting. Both SC and AIC resolve this problem by introducing a penalty term for the number of parameters in the model. For example, the AIC equation takes into account the number of independently adjusted parameters within the model (Akaike, 1974).

The multicollinearity condition number for all models remained around 10. This is not a test statistic per se, but a diagnostic to suggest problems with the stability of the regression results due to multicollinearity (the explanatory variables are too correlated and provide insufficient separate information) (Anselin, 2004). Typically, an indicator over 30 is suggestive of problems (Anselin, 2004). None of the models reached this threshold.

Baseline willingness to intervene remains a significant negative predictor of burglary rate (higher informal control baseline is associated with lower burglary rate), and population difference remains positive (in line with the earlier argument made in relation to the previous model) but also, change in the presence of active guardianship shows a significant negative relationship with burglary rate. This means that in areas where more of the active guardians move away (so the number of active guardians decreases in the daytime) there is a higher burglary rate. In areas where more active guardians remain in the daytime, the burglary rate is lower.

In this way, the fluctuation of active guardians within a temporal time frame (such as the day) can be captured by this data. Therefore with this data it becomes possible to highlight where areas have temporary increases in vulnerability due to the dynamic fluctuation in *active* guardianship levels. This is different than fluctuation in simply the number of people, in line with Reynald's theory that active guardians are those people who are capable and willing to intervene, rather than just those merely present in the environment.

This is further reinforced when looking at the model without population change, only active guardianship and willingness to intervene as predictors.

Both of these variables show a negative relationship with crime, however the log likelihood score indicates a worse model than the one which includes population numbers as well (Table 5.4).

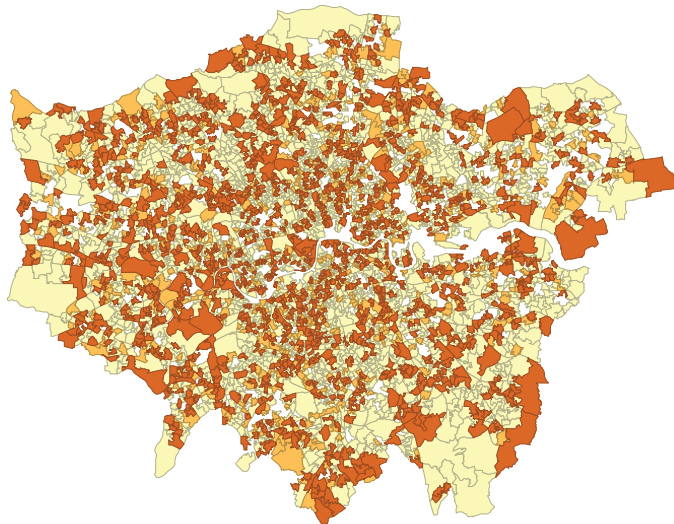
Figure 5.2 further illustrates how the two data sets of population change and reporting change clearly show two very different things; the map showing population change immediately highlights town centres and hubs (especially central London) where the daytime population increases, and all the residential areas where daytime population clearly drops. The map of active guardianship showing changes in levels of FMS reporting does not mirror this at all, and instead shows that there is a spread of neighbourhoods where reporting increases and a spread of neighbourhoods where reporting decreases across London.

Figure 5.2: Change in active guardianship and population between day and nighttime

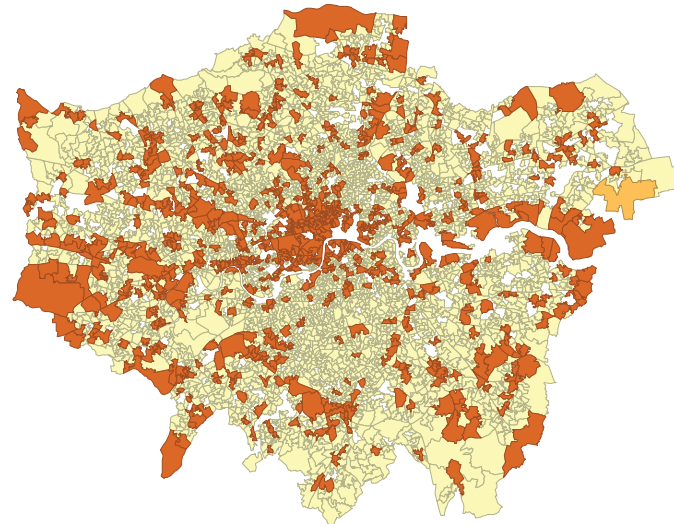
Change between day and night time

- Increase
- No change
- Decrease

Active Guardians



Population



As this crowdsourced data shows where and when the people who are willing to intervene are monitoring their environments, it falls in line with Reynald's measures of active guardianship, and offers a distinct insight into the makeup of the ambient population. It helps identify fluctuation in crime risk due to not the presence of potential targets, but rather the absence of active guardians. By doing so, such crowdsourced data has the potential to scale up active guardianship analysis to large cities, or entire countries, depending on where this data is available. It also has the potential to illustrate short-term temporal variation, such as within-day variation in active guardianship, and map associated fluctuation in crime risk, all using data that is already available, at no cost to the researcher or crime analyst.

5.5 Discussion

This chapter explored the use of crowdsourced geographical data to use in the study of active guardianship. In particular, it should enable researchers to map fluctuation in crime risk not by measuring ambient population, as previous applications of crowdsourced data had done, but by measuring active guardianship to identify when neighbourhoods might become more vulnerable to crime due to the moving away of capable guardians at certain times. Being able to map fluctuation in guardianship across time and place can enable researchers to draw inferences about dynamically changing crime risk. The advantages of such data are already being utilised for measuring ambient and temporally specific populations, but this chapter aims to supplement this by using the qualitative information afforded by such data sets, to interpret different meaning. Beyond just locating people's physical presence in time and space, FMS data implies that these people are those actively monitoring their environments, whose routine activities are congruent with guardianship.

There are many advantages to this data, such as that it is readily available, and requires just some skill to be able to access and compile it to a usable format. It does not require bespoke data collection studies that take time and resources which some researchers and crime analysts may not have. It is also a large data set that covers vast geographical areas, and can be used to study

various places around the globe, wherever there is a platform that people can use to report their grievances online. There are also many limitations, mainly with the bias inherent in the data. These are discussed in detail in Chapter 4, Section 4.4 but must be kept in mind. To address the lack of representation of guardians who are present but monitor in ways other than by participating in FMS, future work could focus on combining this data with the observational measures of guardianship in action, to create a composite measure of active guardianship that could even better reflect levels of willingness to intervene and the preventative effect that active guardians might have in reducing crime risk.

Another limitation of the analysis in this chapter comes from the restrictions around openly available crime data, (discussed in Chapter 3, Subsection 3.6.1). Since the time of the crime incident is not included in this data, the assumption had to be made that more of the burglaries happened in the daytime. Further, the analysis of other crimes, for which on-street population is more important was restricted due to the absence of any temporal data. Future work with more detailed crime data would allow to test fluctuations in FMS reporting against other crime types, to see if results hold up. Such avenues for further enquiry should be pursued, as open, crowdsourced data shows great potential in being useful for mapping not just where and when people are present, but also what these people are doing, how they are interacting with their environments, and what that means for studies in criminology, for estimating crime risk, and applications for situational crime prevention.

Overall, looking at participation in FMS across London neighbourhoods shows an interesting pattern with willingness to intervene, indicating that the people participating are out and about monitoring their environments. Fluctuation in reporting activity can also have indications for increased crime risk due to absence of capable guardians. To inquire into this data further, it is possible to consider not all reporting, but rather only the reporting of issues that can be considered instances of disorder. This subset would give insight into when and where people encounter signs of disorder, those which could be interpreted as signals, in accordance with the signal crimes perspective. The following chapter will explore further the detail of FMS data, to illustrate the potential uses of

crowdsourced data for perception of crime research.

Chapter 6

A dynamic measure of disorder

The previous chapter illustrated the potential for FMS data to represent when and where people were actively monitoring their environments, acting as *active* guardians in their neighbourhood. Due to the fine-grained spatial and temporal resolution of the data, it is possible to measure short-term fluctuation in this guardianship. While Chapter 5 examined the spatial and temporal characteristics of the FMS data (when and where reports were made) based on the active guardianship theories, this chapter investigates the report contents (what were reported) of FMS from the viewpoint of signal disorders (described in Chapter 2, Section 2.3). This chapter aims to take a step further and use the detail made available with the crowdsourced complaints data. By looking at *what* people complain about, it is possible to distinguish signs of disorder from other issues, such as potholes or overgrown trees. This specific subset of FMS reports, those of disorder, have a potential to represent the time and place when people come across *signal* disorders during their routine activities.

On a theoretical level, the link between complaints about instances of *disorder* (such as litter or graffiti) and experience with signal disorders can be made by situating such complaints midway on the spectrum between the two current approaches to measurement of disorder, SSO and questionnaires. To achieve this, Section 6.1 will evaluate two questions: whether complaints reflect observed disorder (SSO) or perceived disorder (questionnaires)? Then, in Section 6.2, I approach the question from a different angle, as perhaps traditional measures do not contain adequate detail. Instead, I use the traditionally established relationship between signal disorders and fear of crime to see whether

more complaints come from areas of higher fear. Then in Section 6.3 I make use of the wealth of detail in this crowdsourced data, to explore people's experiences with disorder during their routine activities. Section 6.4 examines how these experiences vary between different groups. Finally, Section 6.5 offers a discussion of the findings from this chapter, emphasising its role to illustrate how the detail inherent in such crowdsourced data can be used to learn about people's experiences as they go about their routine activities, and how this can be used to gain insight into experiences with signal disorders, and perception of crime and place.

6.1 Testing different measures of disorder

In order to address questions about people's experiences with signs of disorder and the effect that has on their perceptions of crime and place, FMS data can be used. However, first this new data source should be compared with traditional measures of disorder. To achieve this, it is necessary to attain data about disorder collected in traditional ways. Since these data are used only in this chapter of the thesis, I will introduce them here.

6.1.1 Data and study area

As data received from the council is not available for all environmental issues, in this section, only 'rubbish' is used rather than all signs of disorder. So only reports of rubbish are considered. I will therefore evaluate objective SSO measurements of rubbish versus subjective questionnaire measurements of rubbish versus complaints about rubbish in the first section. Rubbish features prominently in the signal crimes narrative. Innes (2014) found that "the dumping of rubbish signalled to residents that an area is 'deteriorating' "(p.29). Further, litter has been found to be a form of disorder impacting upon a lot of people, but fairly diffusely (contrastingly, for example being 'intimidated and pestered' is not something many encounter, although those who do are more intensely affected by it) (Innes, 2014). Evidently, litter is something many people experience, and has the potential to be interpreted as a signal disorder, yet will often not be interpreted so. Therefore an SSO measure of litter can be hypothesised

to over-estimate the extent of signal disorder encounters with the issue. Litter is also the most commonly reported environmental issue that can be considered an instance of disorder (enviro-ASB). Overall there were 182 FMS reports of litter in Camden.

The unique data to this chapter of SSO reports of rubbish is provided by Camden council, and contains systematically collected data about instances of rubbish in the environment. This is collected by Council monitoring officers, who patrol the borough observing instances of rubbish. They typically log between 500-1000 reports of litter per month. For the study period of 4 years (to match the FMS and METPAS data) there were a total of 46,262 reports made by Camden officers. This data represents the SSO method of collecting observed instances of disorder (see Chapter 2, Section 2.3 for discussion of enviro-ASB, and Chapter 4, Section 4.1 for distribution of reports in various categories).

Another data set provided by Camden council contains all complaints made to the council about rubbish for the same time period. This is useful, as it can be used to compare with FMS reports. As discussed in Chapter 3, Subsection 3.3.4, crowdsourced data can be biased in who it represents. It can now be compared against reporting of complaints through all modes to the council, to see how wide the gap between the two sources of data on complaints really is. There are a total of 14,610 reports made by the public about litter within the study time period of 4 years. These complaints were made using online platforms, through sending emails, and over the phone. The majority were made over the phone, making up 84.3 per cent of all complaints. The second most common way for a complaint to come in to the council is via email (13.6%). FMS reports sent to the council would be counted in this category. A separate channel for reporting is Camden Council's own problem reporting online tool, which made up just 1.6% of complaints. 0.4 per cent were made through calls to the Emergency Telephone Service, which means it was a phone call outside of normal working hours (08:00 to 18:00, Monday to Friday), and can come from the police, or a member of the public. The remaining 0.1 per cent were made by people who had to be contacted by a member of the council's

administration team (for example to follow up on an initial complaint) or through a partnership of local businesses.

To measure perceived levels of rubbish in the area, as mentioned in Chapter 3, the METPAS is used as a traditional survey measure. The question used here is worded: 'How much of a problem is rubbish or litter lying around?'. This data represents the purely subjective measure, collected through traditional survey questionnaire approaches. The dataset contains a total of 1174 respondents across the borough. Possible responses are 'Very big problem', 'Fairly big problem', 'Not a very big problem', and 'Not a problem at all'. Responses were coded 1 to 4, with 1 being 'Not a problem at all' and 4 being 'Very big problem'. The aggregate scores for each neighbourhood were calculated by taking the median of the responses from residents within each neighbourhood, in line with Likert scale questionnaire analysis best practice (Clason and Dormody, 1994; Boone and Boone, 2012; Johns, 2010). The median rather than the mean is taken, because this is not a composite score, rather the answer to only one question, so it is an ordinal variable, of ranked qualitative answers. Higher scores mean that the neighbourhood residents perceive rubbish to be more of a problem.

Due to availability of SSO data this chapter also restricts the spatial coverage to the London borough of Camden only, rather than all of London, as is the case in the other chapters. This case study area covers approximately 22 square kilometres in inner London, with almost 210,000 people living in the borough at the time of writing. In terms of socio-economic make-up, it is one of the most polarised boroughs in London with some of the wealthiest areas in England as well as some of the most deprived. Overall recorded crime levels are above the average for London (Camden Council Sites Team, 2012). With these characteristics, this borough presents a good representation of various land uses and populations, as well as an above-average crime rate, which might also indicate a higher presence of signs of disorder, providing enough data to make comparisons between the different methods for gathering information. The borough of Camden is made up of 133 Lower Super Output Areas (LSOAs) which are our unit of analysis (see Chapter 3, Section 3.6).

In terms of analytical approach, as in the previous chapter, a spatial regression model is used, because it is likely that there will be spatial dependence in the data - it is reasonable to assume that neighbourhoods that are near each other have more similar characteristics than they do with neighbourhoods further away. Following the decision process outlined by Anselin (2004), a spatial error was deemed more appropriate for this analysis (p.199). Spatial error accounts for (spatially correlated) co-variates, that if left unattended would affect inference.

Subsection 6.1.2 uses the FMS and council complaints data to investigate first the extent to which complaints made through FMS reflect complaints made through other channels. Then in Section 6.1.3 I move on to use FMS reports about litter to see whether complaints (made through FMS) reflect either of the two traditional measures of disorder in neighbourhoods. I hypothesise that it will be associated with both, but directly mirror neither, and instead point to the measurement of something that can relate to both observed disorder (as it is something tangible in the environment) as well as perceived (something identified as a problem by the person reporting it).

6.1.2 FMS complaints and all council complaints

The data set of complaints provided by Camden council presents an opportunity to determine the extent to which FMS data reflects complaints. These two data sets can be compared against one another. If there is an association between the two, that means that FMS can be used as an approximate reflection of where people make complaints about the environment. As discussed earlier, complaints specifically about litter are used to test this relationship.

A scatterplot of all council complaints and number of FMS reports per neighbourhood shows a positive relationship. This means that there are more FMS complaints coming from areas where there are also more complaints made via any mode of reporting to the council. However, FMS complaints do not account for all complaints made to the council, there are many other factors at play here as well (see Figure 6.1). Most neighbourhoods have 0 or 1 FMS reports, while complaints via all channels are made in much greater numbers.

Figure 6.1: Scatterplot of neighbourhoods by number of FMS reports and all council complaints

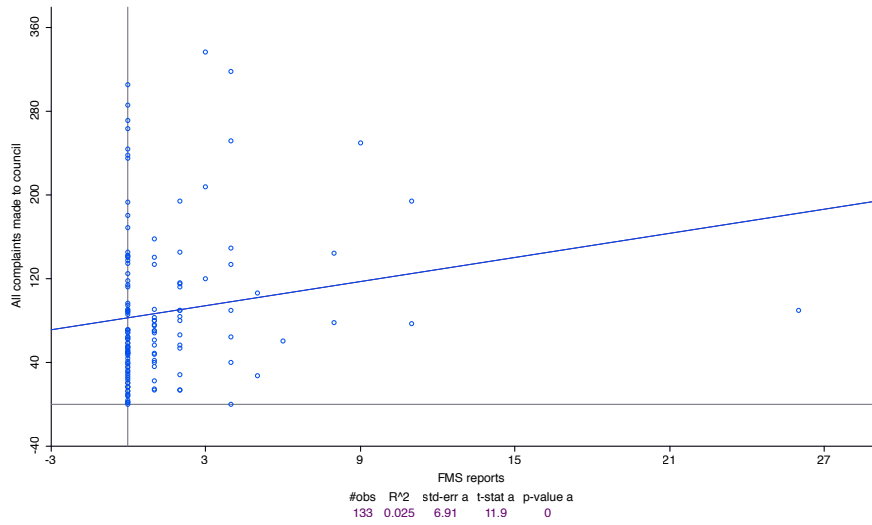
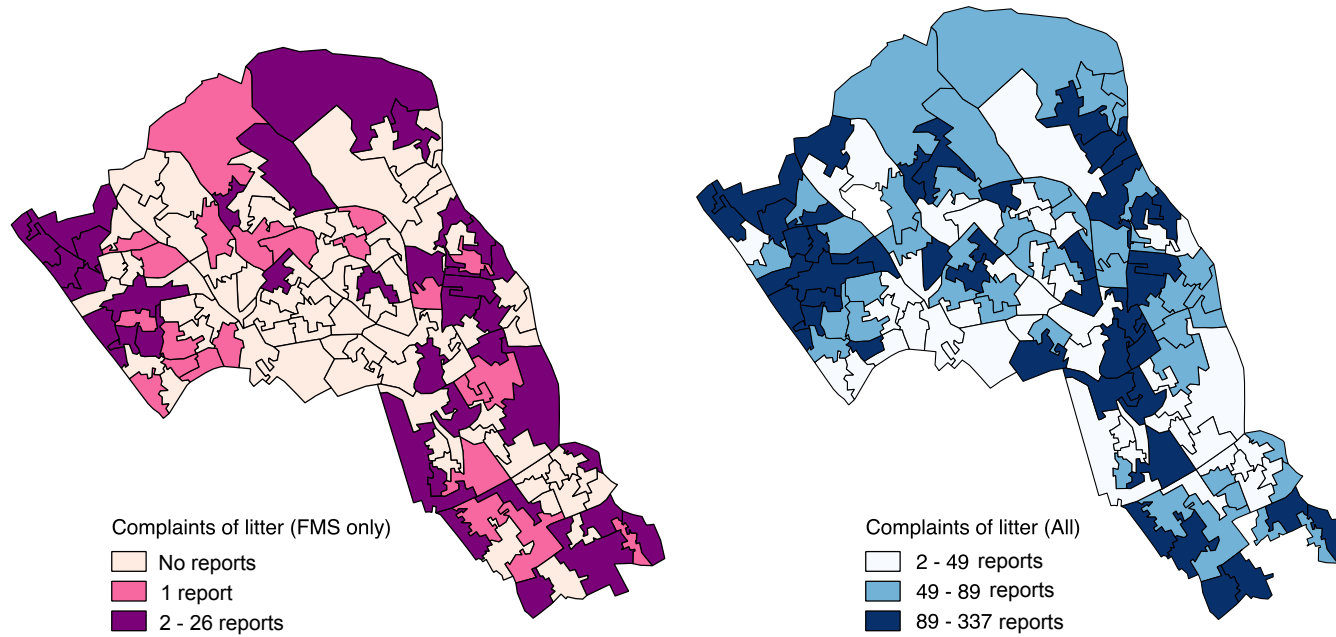


Figure 6.2 further illustrates how while neighbourhoods with higher volumes of complaints also have higher reports from FMS, there are much more complaints in total than only FMS complaints.

Figure 6.2: Complaints reported in total to Camden vs those reported via FMS only



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This finding highlights that FMS perhaps only provides insight into a small portion of complaints, and if complaints reflect people encountering signals of disorder, while FMS captures general trends, it does not account for all of these experiences. However it does provide a sample of complaints, which reflect general levels of complaints (areas with more overall complaints also show up as having more FMS complaints).

6.1.3 Complaints, SSO, and questionnaire measures of disorder

To demonstrate whether complaints litter (measured using FMS) reflect observed instances of litter (measured using SSO), or perceived levels of litter (measured using questionnaires) or something in-between, the first step is to look at the spatially weighted strength of relationships between complaints and the other measures.

Table ?? shows the results from regressing the variables against one another, running six models. These models can then be compared against each other using the Log Likelihood, AIC, and SC values, as described with the spatial regression models in Chapter 5, Subsection 5.2.1. The three models include one to determine the extent to which SSO predicts complaints, one for the extent to which the questionnaire responses predict complaints, and finally one to see whether SSO observations can predict questionnaire answers.

Table 6.1: Spatial error regression model results for different measures of disorder

Dependent variable	Independent variable	Coefficient	p value	R square	Log Likelihood	AIC	SC
FMS reports	Questionnaire	0.029	0.949	0.003	-5967.09	11940.2	11959.1
FMS reports	SSO	0.002	0.10	0.022	-333.630	671.26	677.041
FMS reports	Complaints	0.006	0.067	0.025	-333.364	670.729	676.51
Questionnaire	SSO	0.001	0.73	0.039	-112.619	229.239	235.019
Questionnaire	Complaints	0.001	0.22	0.046	-111.936	227.873	233.653
Questionnaire	FMS	-0.002	0.88	0.039	-112.667	229.334	235.115

Interestingly, perceived levels of rubbish in a neighbourhood do not significantly predict the number of FMS reports. This is the worst fit model according to the log likelihood, AIC, and SC values. SSO observations of rubbish do show a positive association with number of FMS reports, and the model shows a much better fit than did the model using questionnaire values as a predictor variable. Finally, complaints made to the council are the best predictor of complaints made through FMS. This reinforces the finding in Subsection 6.1.2, and provides feedback indicating that the crowdsourced data reflects trends from the official data sources.

Looking into the other relationships, I use the perceived levels of rubbish as the dependent variable, and consider separate models for each predictor variable to compare their relationship. Interestingly, I find no significant relationship between SSO levels of rubbish and the extent to which people subjectively perceive something to be an issue. Evidently, something other than merely the presence of observable instances of disorder drives people's perception of their neighbourhoods. Complaints produce a model with a slightly improved fit. Although these predictors are not statistically significant at a 95% confidence level.

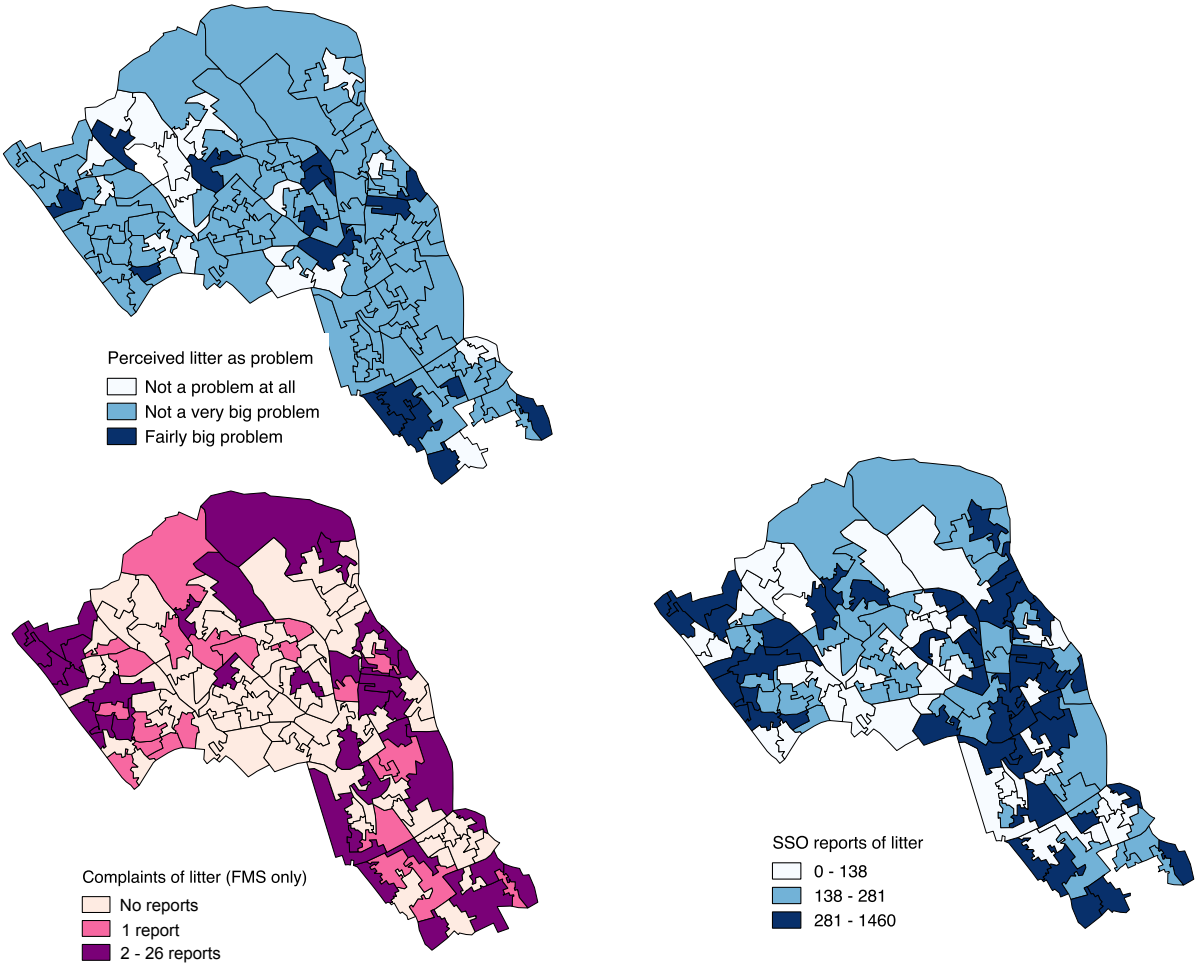
Results show that there is not a significant relationship between levels of perceived disorder (measured using questionnaire) and complaints measured with FMS, nor observed disorder measured with SSO. This means that there is essentially no relationship between perceived levels of rubbish in a neighbourhood based on the METPAS questionnaire survey, and levels of rubbish recorded through complaints to the council, or observed through council officials logging all instances of litter.

On the other hand, the association with observed litter measured using SSO data is significant at a 90% confidence interval ($p = 0.10$). This means a spatial association between complaints and observed cases of disorder recorded through SSO can be made. However the incredibly small coefficient implies that there is a filter introduced with complaints, whereby not all cases of observed disorder are reported in complaints, rather residents select for themselves what they choose to report. It remains possible that this selec-

tion of what they report can be based on the extent to which they perceive the issue to be a problem. Crucially, the positive relationship between complaints and SSO/ survey responses does not show perfect linearity. This demonstrates that the complaints data does not purely replicate either measure.

The most interesting conclusion to draw from the above results is that all three measurements of rubbish in Camden show a different picture. Figure 6.3 shows that while complaints and SSO reports highlight similar neighbourhoods having higher number of reports, that number is very different. There are thousands of instances of disorder logged by SSO observers, while only a few submitted as complaints via FMS. However, the map of perceived levels of disorder shows an entirely different image to both complaints and SSO; most neighbourhoods have an average score of 'Not a very big problem'. While some neighbourhoods have perceived levels of rubbish at 'Fairly big problem' level and also appear in the high SSO and high complaints category, this co-variation is not affirmed by the spatial regression, and therefore we cannot conclude there to be a significant relationship.

Figure 6.3: Complaints of rubbish vs perceived and observed levels



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Contains data from Camden Council
Contains data from www.fixmystreet.com

Using this example of citizen complaints about rubbish in the case study borough illustrates that crowdsourced data about where people encounter issues of disorder, which they deem problematic enough to take a behavioural response and report, reflects something different to observed *or* perceived levels of disorder. While associated with observable instances of disorder (measured with SSO), the FMS data appears to be a 'filtered' measure that reflects where (and when) people encounter instances of disorder that they interpret as problems during their routine activities. It can be argued that these encounters might affect their perception of place. However, with the above results, we cannot conclude that complaints reflect perceived disorder (as measured by METPAS) we can only say that observed disorder is filtered through the subjective interpretation of a 'perceiver' who evaluates something as an issue worth reporting to the council.

The next section will, therefore, take a different approach, using the established link between signal disorders and the fear of crime, to explore whether more complaints are associated with higher rates of worry.

6.2 Complaints and the fear of crime

Researchers working on the topic of fear of crime in place have established a firm link between disorder and fear of crime (see Chapter 2, Section 2.3). Therefore it is possible to hypothesise that if complaints reflect people interpreting an issue as a signal, which can lead to increased fear, then more complaints should come from areas with higher rates of fear of crime.

The dependent variable for this section is a fear of crime score derived for each neighbourhood using the METPAS. The METPAS question used is: 'To what extent are you worried about crime in this area?'. Possible answers are 'Not at all worried', 'Not very worried', 'Fairly worried', and 'Very worried'. In the exact same way as the above, responses were coded 1 for 'Not at all worried' and 4 for 'Very worried', and aggregate scores for each neighbourhood were calculated by taking the median of the responses from residents within each neighbourhood (Clason and Dormody, 1994; Boone and Boone, 2012; Johns, 2010). Higher scores mean that residents of that neighbourhood rated

feeling more worried about crime. Similarly to perceived levels of rubbish in Section 6.1, as it is a single item question, the median is used, as it is a more appropriate measure than the mean.

The independent variables used to regress against fear of crime score (calculated as discussed above from the METPAS survey results) are the same as the ones used in the previous section, including SSO, questionnaire, and complaints measures of rubbish. However, in order to explore the relationship between fear of crime and all signal disorders, I also include an additional predictor, the reports of all issues that fall under the umbrella of enviro-ASB. So not only litter, but also graffiti, dog fouling, noise complaints, and abandoned vehicles, as detailed in Chapter 3, Section 3.6. Further, to account for the different levels of reporting (perhaps FMS is more widely used in some areas than others) I also consider the *proportion* of reports that are enviro-ASBs. Thus I take all FMS activity in a neighbourhood as a baseline, and then I filter, how much of these are actually reports about enviro-ASBs versus other issues like potholes. Results are presented in Table 6.2.

Table 6.2: Spatial Error Regression Model Results for worry about crime

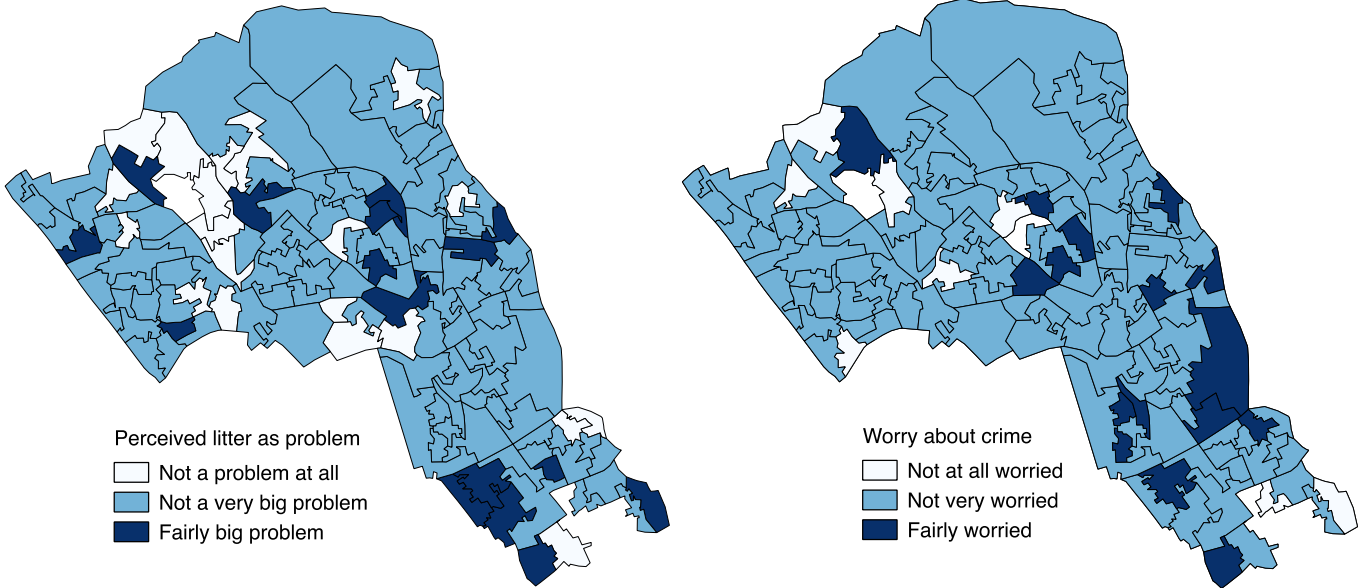
Independent variable	Coefficient	p value	R square	Log Likelihood	AIC	SC
SSO	-0.001	0.99	0.002	-101.65	207.294	213.075
Questionnaire	0.3	0.001	0.111	-93.96	191.922	197.703
All complaints about litter	-0.001	0.92	0.003	-101.64	207.284	213.065
FMS complaints about litter	0.003	0.83	0.003	-101.63	207.251	213.032
FMS complaints about all enviro-ASB	-0.003	0.77	0.003	-101.605	207.21	212.99
Proportion of all complaints that are about incivilities	0.001	0.006	0.078	-101.52	207.005	212.785

The only variables that show a significant relationship with worry about crime are the questionnaire measure of perceived disorder and the proportion of all FMS reports in the neighbourhood that were about enviro-ASBs. Comparing the log likelihood, AIC, and SC scores, the model with the best fit is the one that has perceived levels of litter as a predictor variable. This is in line with prior findings about perception. It can be argued, as was done in Chapter 2 that this measurement reflects general anxieties, and that the question about perceived litter does the same, rather than anchor these perceptions in people's everyday experiences. Therefore it is not surprising that these measures are related.

The model with the second best fit is that with the proportion of all reports that are incivilities as a predictor. However the performance of this model is not much better than the others. However this is the only other model where the coefficient has a significant p value. This coefficient is very small, but has a positive sign, which means that where more of reports are about signal disorders, there are also slightly higher levels of reported fear of crime. However, the effect remains very small.

Visualising the relationship between questionnaire responses to perceived levels of litter being a problem, and worry about crime reveals that most neighbourhoods score about the same on both, where participants select the second option (either 'Not a very big problem' or 'Not very worried') most of the time (Figure 6.4).

Figure 6.4: Perceived rubbish and fear of crime



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Contains Ordnance Survey data © Crown copyright and database right [2015] Contains data from Metropolitan Policia Public Attitudes Survey

This is consistent with the central tendency bias, which refers to survey respondents over-selecting of the mid-range options (Malone et al., 2014). This can occur when collecting data using a Likert Scale. Often respondents tend to move towards the middle of the scale (Malone et al., 2014). While this bias mostly affects scales with a neutral middle point (for example those with 5 options to choose from), it still affects responses not falling on the more peripheral options (Not at all worried, or Very worried) and so the aggregate response per neighbourhood will tend towards these more neutral options. Therefore using this measure might not represent the variation in people's experiences very well.

Another issue comes from the result of the aggregation of questionnaire results to neighbourhood levels, masking lower level variation. In their study using METPAS data at LSOA level, Sutherland et al. (2013) found 91 per cent of variation in levels of collective efficacy occurred *within* neighbourhoods, and propose that this might help to explain the weak relationships they found between variables. As they put it: "in essence we may be operating at too high a level of aggregation" (p.17). This could also explain why there is no relationship seen between questionnaire measures of perceived disorder and the number of complaints made at this spatial aggregation level of neighbourhoods. This assumption might also explain why there is no relationship showing up between observed disorder (SSO) and perceived levels of disorder (questionnaire), and the complaints, as well as between SSO, complaints, and worry about crime.

To address this, an exploration of lower-level variation in experiences with disorder is required. While we cannot conclude that the crowdsourced complaints data reflects people's perception of perceived levels of a particular issue in their area as measured with questionnaires, it emerges that it is some sort of filtered collection of observed instances of disorder. It is possible that this filter is the interpretation of something as a signal of disorder. Indeed, there seems to be a positive association between more reports about enviro-ASB issues and fear of crime in a neighbourhood. This relationship is only slight.

The next section (Section 6.3) will explore more fine-grained variation in people's experiences of disorder using the enviro-ASB reports from the crowd-

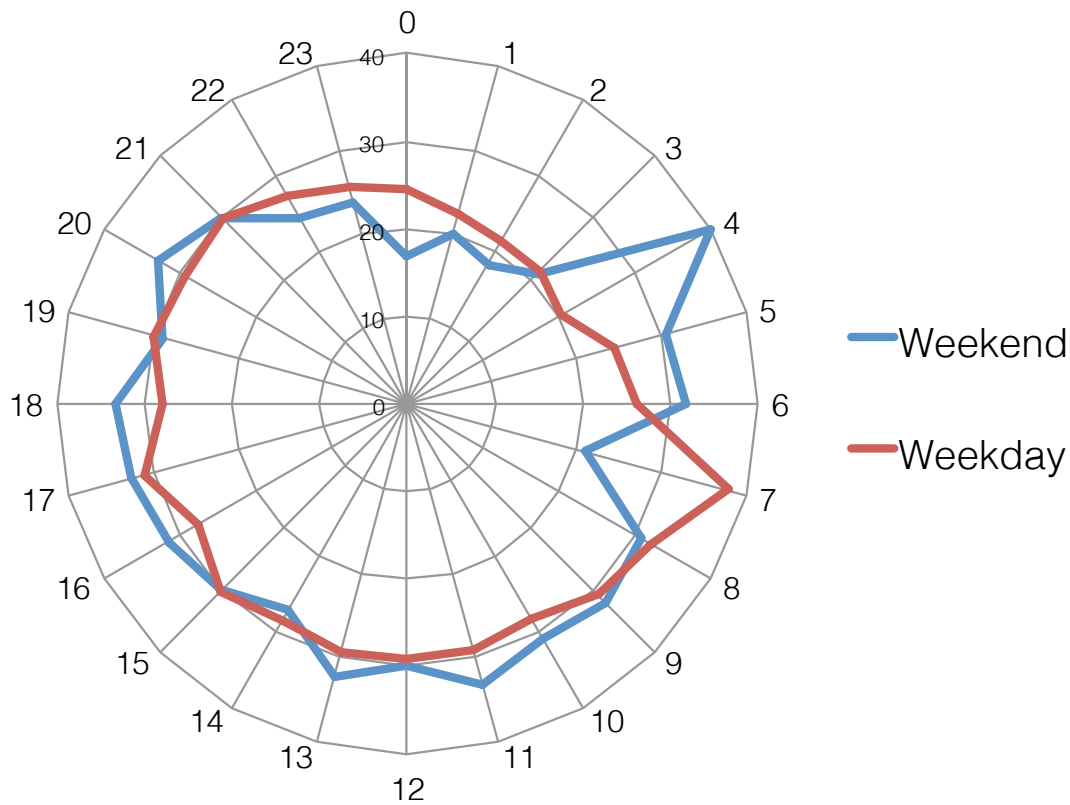
sourced FMS data. By looking at micro-level changes in reporting both temporally and spatially, it is possible to learn more about what it is that can be influencing people's experiences with disorder during their routine activities.

6.3 Exploring experience with disorder in place and time

As discussed in Section 6.2, people do not report all issues of disorder they encounter using FMS. Instead they use some filter, and only report some issues that they consider problematic, and would like the council to clean up. It is possible to use this data to find out more about instances of disorder that people encounter during their routine activities, which they respond to in a way that indicates an interpretation of the issue as a problem worth noting.

A possible shortcoming of measuring experience with disorder at a neighbourhood level is that aggregation might mask smaller scale variation. This was mentioned in Section 6.2 as a possible reason for no association between complaints and perceived levels of disorder, or even observed instances of disorder collected using SSO and the perceived levels of disorder and fear of crime. However the crowdsourced FMS data contains spatial and temporal resolution low enough to explore these variations, and this is what this section will present.

One line of inquiry is to explore temporal fluctuations in when people encounter these signs of disorder. The granularity of this crowdsourced data allows to go past the day versus night dichotomy usually employed by surveys. It can pinpoint exactly when such experiences can occur, and so can highlight specific time periods where a targeted intervention could prevent experiencing signs of disorder. Looking at temporal variation in the proportion of incivility reports shows that during most of the day both on weekends and weekdays, incivilities make up just under one third of all FMS reports (Figure 6.5), and this stays relatively stable during the day.

Figure 6.5: Percentage of all FMS reports about incivilities.

However, an interesting deviation is a peak at 7am on weekdays (Figure 6.5) when disorder reports make up 40 per cent of all FMS reports. This means that at 7am on weekdays, people encounter higher rates of signal disorders than other things or at other times. Interestingly, this is contrary to what was expected; the assumption was that late night and very early morning would be much more problematic, based on images of increased fear 'after dark'. In order to understand and explore this further, it is possible to utilise the wealth of information included in such crowdsourced data, and read through the descriptions provided with these reports. It appears that the majority (83%) of these are litter complaints (n=319), mostly about overflowing bins. The narrative descriptions included in the FMS reports data set reveal that these reports were made by people who went to work in the morning, and encountered signs of activity that took place in the same location, but at a different time (for example see Figure 6.6). Some examples of these reports are:

- *At the start of west view footpath the side which the claddagh ring bar is near every night drunk hooligans congregate behind the businesses little*

discard their fried chicken boxes beer cans

- *There are lots of stray people coming and throwing their Cans Bottles here in spite of spending our own money and getting it cleaned. This has to be prevented ASAP.*

People apparently see signs of another activity in the areas where their routine activity pattern takes them through at a different time. And as these signs are attributed meaning of neglect and possible breakdown of the social order, and therefore act as signals, which can result in people experiencing fear of crime. People apparently saw signs of another activity in the areas where their routine activity pattern took them through at a different time. And as these signs are attributed meaning of neglect and possible breakdown of the social order, and therefore act as signals, which can result in people experiencing fear of crime. The finding that people use artefacts of certain activities in a space to make inferences about it is notable and will be discussed in Section 6.5.

Besides the fine-grained temporal resolution, this data also allows us to map at a micro-geographical level where people are more or less likely to encounter signal disorders and potentially experience fear of crime.

The spatial statistic G_i^* can be used to compare local averages to global averages, to identify if the local pattern of crime is different to what is generally observed across the whole study area. Getis-Ord G_i and G_i^* are a local clustering test presented by Getis and Ord (1992), based on the concentration of values in the neighbourhood of a unit. The G_i^* matches the usual definition of cluster as a contiguous and non-perforated set of units. A positive value indicates clustering of high values and a negative value indicates a cluster of low values (Fischer and Getis, 2009). The results here will be presented in maps of these clusters in Figures 6.7 and 6.8. Significant clusters (at $p = < 0.05$ are highlighted in red if they have a positive value (i.e. a cluster of street segments with many FMS reports about disorder), and highlighted in blue if they have a negative value (i.e. a cluster of street segments with low (possibly zero) FMS reports about disorder).

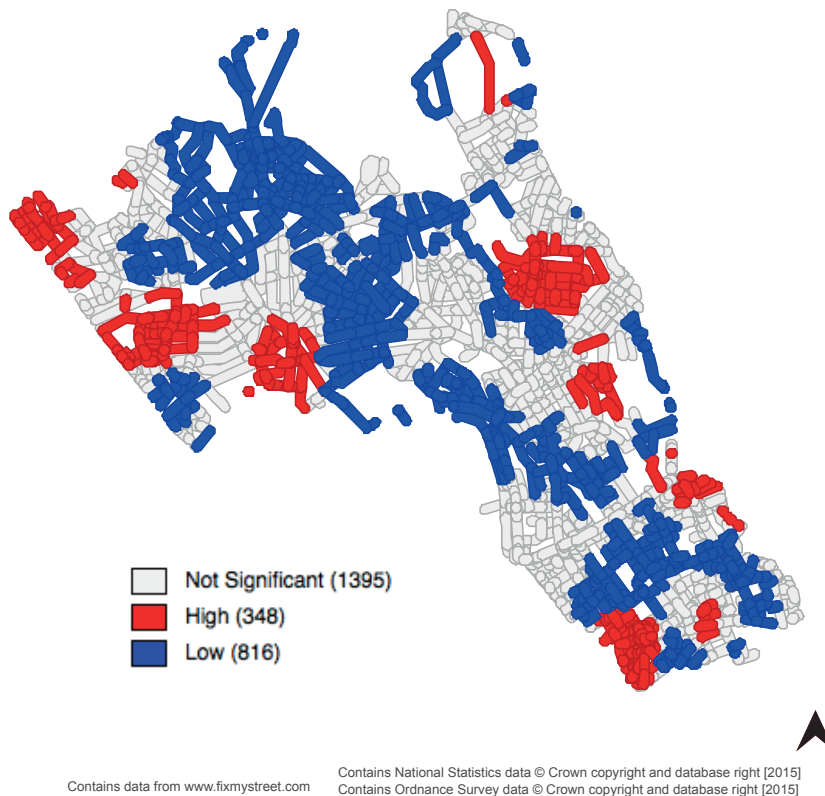
G_i^* scores (here using street segments in our case study area as the unit

Figure 6.6: FMS report about 'over flowing rubbish, street drinkers, litter in the street and rats'



of analysis) reveal significant clusters of street segments (those in red) where there is a high proportion of reports being about enviro-ASBs, which indicates more opportunities for people to come across signal disorders and experience fear of crime events (Figure 6.7).

Further, it is also possible to see how these clusters of segments shift over

Figure 6.7: Gi* map of FMS reports that are incivilities

time with the changes to people's routine activities. For example, the changes in travel patterns during the day can be considered. Based on travel patterns in London the day can be split into six main groups: early morning (4am to 7am), am peak (7am to 10am), inter-peak (10am to 4pm), pm peak (4pm to 7pm), evening (7pm to 10pm) and night (10pm to 4am) (Transport for London, 2014b). Figure 6.8 shows how the clusters of segments where people are encountering potential signal disorders varies between these time periods.

Figure 6.8: Variation in hotspots of signal crimes within the day

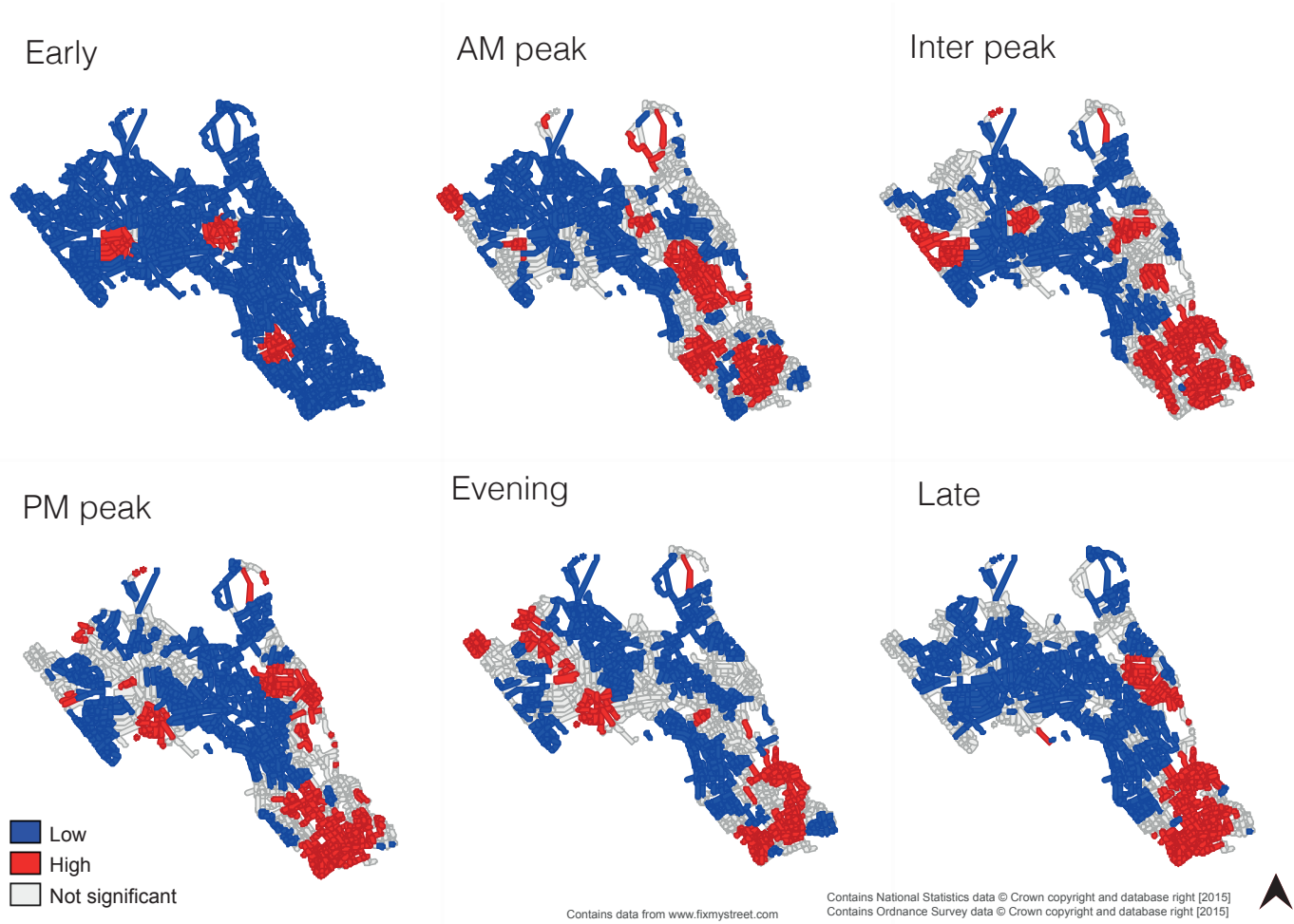


Figure 6.8 illustrates not only that where people report instances of disorder clusters in place, but also that these clusters move about between different times of the day. In the very early hours, essentially the entire borough is one big negative hotspot (or cold spot), as there are not many reports, and people are sleeping. However in the midst of that, there are still significant clusters of high reporting. In the am peak, the southern part of the borough begins to emerge as a cluster of more incivility reports, and this cluster strengthens and then persists throughout the day. This is in line with land use in this area of Camden, this area is a busy central area with shops and bars that attract people. However other clusters come and go during the day, and this sort of variation is interesting to explore. This means that people's experiences with signs of disorder fluctuate dynamically over both place and time. And this crowdsourced data on reporting environmental issues is able to show this dynamic variation. It is possible then to highlight these areas for further inquiry, to examine what it is in these places that people are reporting, and why that changes over time.

This section has illustrated the spatial and temporal variation in when and where people encounter signs of disorder as part of their routine activities. This section showed how complaints about disorder concentrate in space, and this spatial clustering changes with time of day, indicating that when and where people encounter signs of disorder varies in both place and time. Section 6.4 will now explore between-group differences in experiencing disorder, using the name of the person doing the reporting to infer characteristics, as described in Chapter 4, Section 4.3.

6.4 Between group differences in experience with disorders

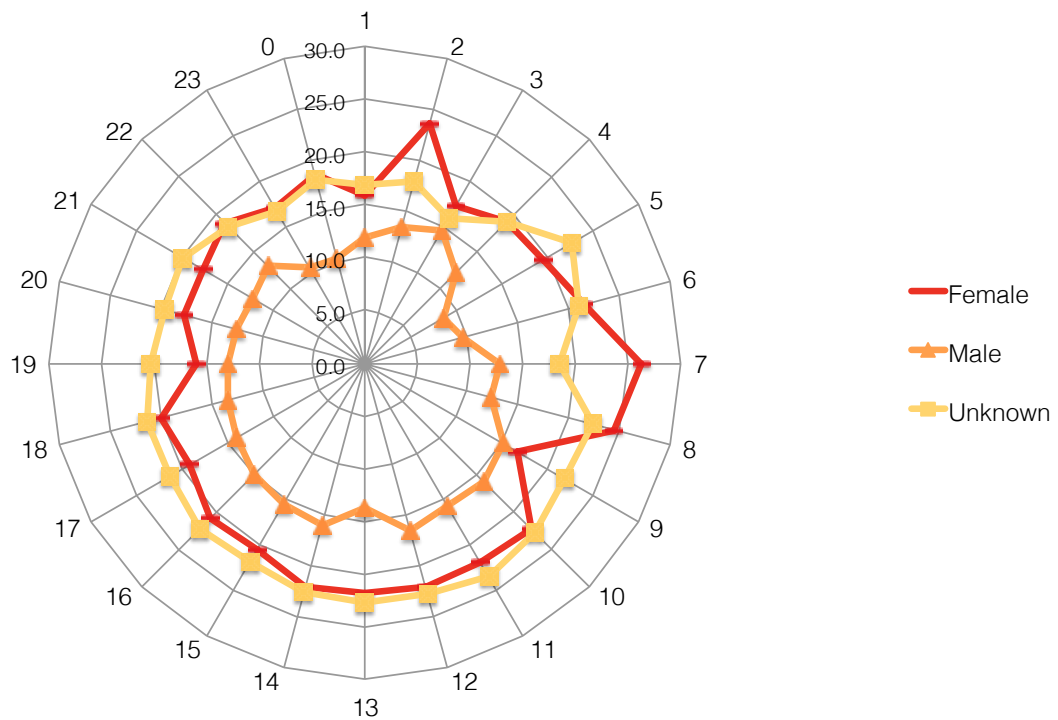
As well as using this data to tell us about when and where people encounter instances of disorder that they respond to, it can be also used to gain insight into the people doing the reporting. Much research in fear of crime has looked into differences between different demographic groups in their experiences of

fear. One demographic variable that has been found to have an effect on people's perception of crime and safety and their neighbourhoods is their gender (Davenport, 2010). If possible, it would be interesting to use the FMS dataset to be able to look further into these differences in reporting of enviro-ASBs. As mentioned in Chapter 4, demographic information about people who provided their names with their reports can be inferred, provided the researcher is willing to accept some assumptions and take some risks.

Using the classification of people into either men or women based on their names makes it possible to explore between-group differences in reporting disorder. A chi-square test reveals that there is a relationship between gender and reporting. Reports about enviro-ASB issues are made more by women, whereas men are more likely to report non-incivility issues ($\text{chi-square} = 1614.343, df = 2, p\text{-value} < 0.001$). Thus while there are fewer reports from females (see Chapter 4), these are more likely to be about incivilities than reports made by males. This finding is in line with results from ASB victims survey data from Innes (2014) who found that women, on average, attend more carefully to physical disorder signals.

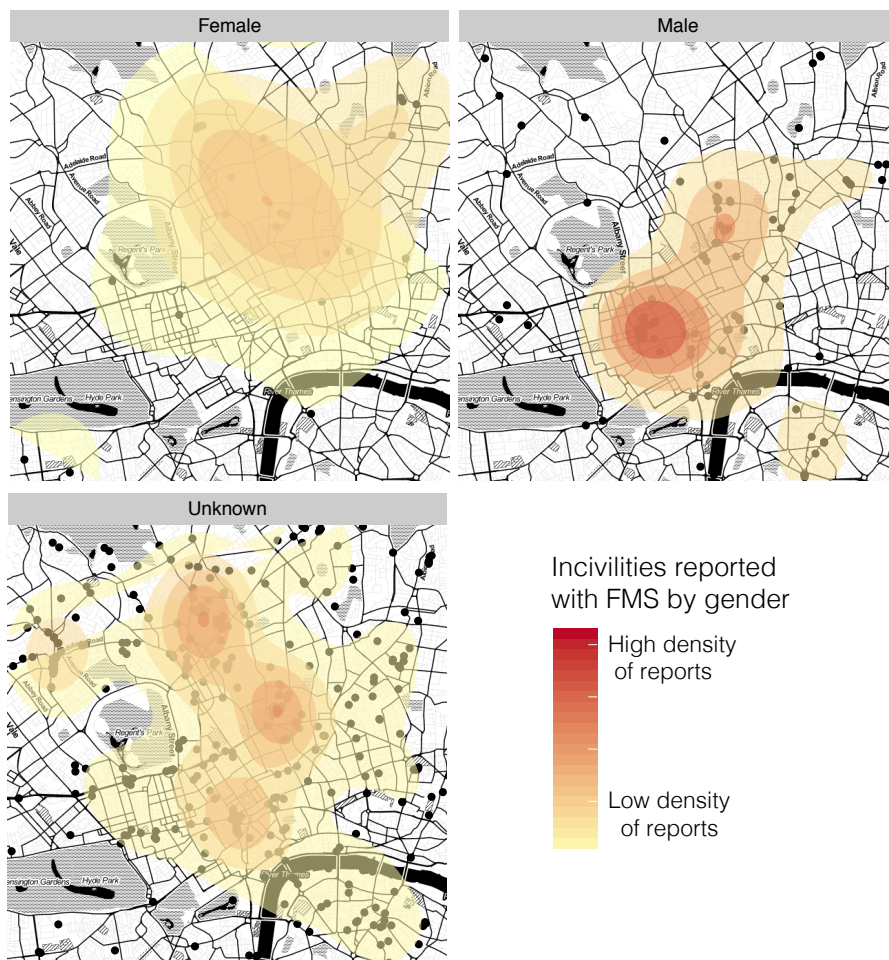
In fact, considering the proportion of reports that are incivilities during the different hours of the day reveals that this trend remains steady over the course of the day, with the exception of 3am when there is a drop in the percentage of reports about incivilities for women but a peak for men, and at 9am when men's reports of incivilities actually stays constant, but women experience a drop (In Chapter 4 I supported the assumption that time of report reflects approximately when people experience the issue they report, but this remains an assumption nevertheless). However this temporal fluctuation is small, and it appears that consistently around the clock about 15-20% of reports made by both female and anonymous reporters, and between 10-15% of reports made by male reporters are about incivilities in each hour of the day (Figure 6.9).

Figure 6.9: Proportion of FMS reports that are about incivilities by gender during hours of the day



This variation over time suggests that *when* women experience proportionally more incivilities does not correspond with the times that men do.

Further looking at whether their experiences vary spatially, it is possible to look at the hotspot mapping of incivilities in the central London area, and break the maps down by gender (Figure 6.10).

Figure 6.10: Hotspots of incivility reports with FMS in central London area by gender

Here the 'unknown' category refers to anonymous reports and those made by people who could not be assigned a gender based on their name (see Chapter 4). However looking at the other two maps reveals a difference between men and women, indicating that where each group experiences incivilities actually varies. Men apparently notice enviro-ASBs in different places than women, which can have differing impacts on their perception of the environment, and consequent feelings of safety.

As mentioned, this finding is in line with analysis of interview transcripts by Innes (2014), which appears to imply that women attend more to physical disorder, whilst men are scanning more for the potential for violence (or in the case

of disorder, potential for some harmful consequence to them or their property such as a vehicle) (Innes, 2014).

It is possible to use the FMS data to explore this in even more depth, and look at specifically what categories men and women are over- and underrepresented in. Looking at differences in reporting in different categories shows that there is a significant gender difference in reporting within the categories ($\text{chi-squared} = 4822.301, df = 58, p\text{-value} < 0.001$). The table of standardised residuals (Figure 6.11) reveals that reports about parking, abandoned vehicles, graffiti, highway issues, hazards, and carriageway defects were most likely to be reported anonymously. Reports about dog fouling, greenery, litter were more likely to come from women or anonymous reporters, while reports about dead animals, parks, and public toilets were more likely to come from women. People who left their name were more likely to report street cleaning issues than anonymous reporters. And finally, reports in unclassified, potholes, pavement or road issues were more likely reported by men. It appears then that there is somewhat of a gender divide in reporting within certain categories. On first glance at these it is an interesting thing to note that from men there are more reports in categories related to driving (for example potholes and road problems), whereas women are more likely to report about categories related to walking (for example parks, dead animals, dog fouling, litter). There is great potential scope for exploring this further for researchers interested in the role of gender and the use of public space.

Figure 6.11: Chi-square standardised residual table of number of reports in FMS categories by gender (anything greater than 2 or below -2 is a meaningful difference)

	Female	Male	Unknown
Abandoned or untaxed vehicle	-6.14	-22.14	23.90
Bridge issues	-0.78	-0.42	0.85
Bus shelter issues	2.06	-0.24	-1.01
Carriageway defect	-2.67	-4.07	5.31
Dangerous structure	1.92	-1.86	0.56
Dead animal	4.75	-6.52	3.12
Debris	-0.31	-2.90	2.84
Dog fouling	9.31	-19.37	12.15
Drainage	-2.19	-1.31	2.50
Environmental health	1.40	-2.14	1.12
General maintenance	3.22	-3.29	1.08
Graffiti	-6.27	-5.38	8.65
Greenery	6.29	-14.29	9.31
Gullies or manholes	-0.80	-3.13	3.33
Hazards	-1.20	-6.58	6.73
Highway issues	-2.04	-7.13	7.73
Litter	4.89	-26.84	21.62
Miscellaneous	2.58	2.60	-3.91
Parking	-6.88	-22.75	24.90
Parks	3.66	-3.60	1.10
Pavemen or road issues	-0.22	5.77	-5.15
Potholes	-4.73	23.63	-18.78
Property damage	-0.12	-1.61	1.54
Public right of way	0.50	3.16	-3.19
Public toilets	3.64	-5.67	3.01
Signage	2.27	3.11	-4.20
Street cleaning	3.44	8.37	-9.70
Street furniture	-1.13	0.55	0.17
Street lighting	-2.37	1.42	0.11
Traffic lights	-2.16	2.09	-0.62
Unclassified	-3.50	38.19	-32.82

Future qualitative inquiry into this difference in FMS reporting behaviour

by gender would also be useful in terms of identifying potential gender bias in such data sets.

Overall, while obviously subject to some limitations (discussed in detail in Chapter 4), such crowdsourced data about people's perceptions of disorder can be used to identify differences in how people experience their environments. This data, for example, can be used to highlight areas for further analysis to look into the built environmental characteristics of different hotspots found in Section 6.4.1, and consider between group differences in what signals are attended to, found in Section 6.4.2, to ensure situational interventions address perceptions of safety for all.

6.5 Discussion

Throughout this chapter FMS data has been used to explore people's everyday experiences with disorder as they go about their everyday routine activities. Section 6.1 compared the data with other measures for disorder, and concluded that it shows something distinct to what is currently captured using surveys or systematic social observation. Further it confirmed that the crowdsourced complaints data roughly reflects the official complaints data, which is reassuring for the use of such data. Then Section 6.2 explored the relationship between the various measures of disorder with levels of fear of crime in neighbourhoods, finding that questionnaire measures of perceived rubbish best reflect questionnaire measures of disorder, followed by the proportion of reports which were made about enviro-ASBs.

Section 6.3 explored people's experiences with disorder using the FMS data to gain new, interesting findings. The insight into where and when people encounter signal disorders during their routine activities has great implications for preventative situational approaches to reducing the fear of crime. For example, in Section 6.3, analysis of crowdsourced reports of enviro-ASB highlighted that people experience signal disorders as and when they encounter them during their routine activities, and not necessarily when they stray from these routine activities. For example, many reports were made not during late night or early morning hours when the antisocial behaviour is taking place, but

rather when the 'perceivers' encounter the 'aftermath' of this behaviour. This aftermath can be understood as the signals left behind, which the perceivers interpret as problematic. Even though these different users of the space might not cross paths, so the people who feel fearful might not actually witness the behaviour that causes this fear, it is the *signals* left behind that have an effect on the perceiver, resulting in potential fear of crime in these locations. This finding highlights the importance of perception; even though the act of the enviro-ASB (such as littering or graffiti) may have taken place the night before, the consequences on the person who is perceiving it as a sign of disorder are not actualised until the following morning when their routine activity takes them through that space. Thus even though the offender was in that environment at a specific time, it is not until later that it affects the passer-by perceiver.

If such experiences can be considered to be linked with increased feelings of fear of crime, there are implications of this finding for reduction in fear and its negative consequences. This data can be used to identify times and locations where such 'hand over' of place occurs between different 'users', and target these times, to ensure that signals are not left behind for perceivers. For example, if it can be known that those who are out at night tend to retire from an area at 4am, and the new users do not appear until 7am, the signals left behind could be cleaned up in the time before the new users of the space arrive. In fact when it comes to addressing fear of crime, it may be as effective to prevent a perceiver from seeing something they can interpret as a sign as it would be to prevent the act that created the signal in the first place. This could help reduce fear and its harmful consequences by improving perceptions of the area. Mapping these experiences in the micro-scale geographical resolution could highlight hotspots of concern, and identify areas where further research can be done to determine what is it about these areas that facilitate opportunities for people to encounter things which make them afraid, and what is it about the other places where these experiences are less likely to occur, to inform prevention and design.

Finally, Section 6.4 explored between-group variance in experience with disorders, showing that experiences with disorder vary systematically between

groups. This is important to consider as it might be linked to people's routine activities, or to the consequences of encountering signs of disorder, such as fear of crime.

An avenue for future research is to use openly available online data sources to gain insight into other elements of people's perception of their environments. For example in their study utilising community intelligence mentioned earlier, Innes et al. (2009) asked participants to plot on the maps the boundaries of what they consider to be their neighbourhoods (Innes et al., 2009). Perhaps if it were possible to map participation in various online forums, inferences could be made about geographical location of communities with shared interests, which could help further guide engagement strategies. Further, semiotic cluster analysis could be performed on the comments and detailed descriptions also provided with each FMS report, to be able to tease out the themes which reports fall into beyond just separating them out by title (Innes, 2014). Further the text can be also examined to explore the meanings attached to the different problems, and how they might vary with situational contexts for example different time of day or day of week (Innes, 2015). This could provide further insight also into the spatial accuracy of the data. For example, Kinsella et al. (2011) demonstrate how it is possible to verify the accuracy of a geotag, or even locate data with no geotag attribute by using the descriptive text in the data.

As detailed in reference to crowdsourced data generally in Chapter 3, and also demonstrated throughout the use of FMS data in these Chapters 4, 5, and 6, there are various assumptions that must be made about the data to use them for research purposes. Calling into question these assumptions can call into question the validity of these measures. To address this, one approach is to run a bespoke data collection method, to ensure that all necessary data is collected to answer research questions. In the following chapters, one such approach will be explored, by applying the methodological framework of this thesis to measuring fear of crime directly, in a way that reflects fear conceptualised in line with our routine activities based definition.

Chapter 7

Developing a tool for a dynamic measure of fear of crime

While the previous chapters demonstrated the great potential of using crowd-sourced data to measure experiences during routine activities, as discussed in Chapter 3 such data has its own set of limitations, and Chapter 4 confirmed that FMS data is no different. One of the issues discussed is that the researcher has no say in the design of the data collection method, and therefore the information provided might not always cover all variables that need to be measured. While sometimes this can be addressed by combining various data sets, for example as was done with the names database to infer demographic characteristics in Chapter 4, Section 4.3, this approach is less direct and therefore open to errors. However, generally the researcher has no say on what data is collected, and instead, must make do with what is available (Boyd and Crawford, 2012).

To address this, it is useful to explore the potential of creating bespoke measurement tools to collect data directly about the phenomena of interest. This chapter serves to explore the possibility of taking traditional approaches to directly measuring the fear of crime, and applying the advances in research tools afforded by mobile technology to their deployment. First, Section 7.1 will detail the development of the application prototype. Then Section 7.2 discusses the development and trial of a bespoke data collection application, and Section 7.3 details results of pilot testing and changes that needed to be made as a result. Finally Section 7.4 addresses the ethical issues that must be considered when building and deploying such a tool. Section 7.5 offers a discussion of the

application design and testing process, highlighting the ability of this chapter to serve as a guide for future researchers who wish to employ such approaches in the future.

7.1 Fear of crime application prototype development

As mentioned in Chapter 2, Subsection 2.2.5, in this research fear of crime is framed as a situational experience by applying the framework of routine activities. People move about their activity space, and they occasionally encounter something in their environment that can act as a signal, and if interpreted as such, can evoke an experience of fear. However these people then move into different situational contexts, and this fear diminishes. A contribution of this thesis is to posit that fear of crime occurs at the intersection of the necessary situational factors. Chapter 2 Subsection 2.2.3 argued that current measurement approaches to collecting data about the fear of crime do not reflect such dynamic within-person variation with changes in situational context. This is also hard to do using crowdsourced data such as FMS, as it is very difficult to use this to track individuals' behaviours and perceptions longitudinally. To address this, this section will apply the innovations described in the methodological framework to develop a bespoke measurement tool to record fear of crime over time. The aim is to create a measurement tool that can collect data to empirically reflect how fear of crime varies between situations, rather than being a static feature or characteristic of people.

This section summarises the development of the Fear of Crime Application (FOCApp). A systematic 4 stage approach was taken to its development. In the first stage, the concept of fear of crime experience needed to be operationalised. Chapter 2 Section 2.2 outlined the theoretical approach to this, however the potential for people to interpret and map their experiences with fear of crime in place and time needed to be confirmed. Subsection 7.1.1 presents this process. Then Subsection 7.1.2 describes the process of questionnaire development. Two approaches are trialled, one where the traditional CSEW question

is used (Office for National Statistics, 2014), and the approach used in experience sampling applications asking participants to report their feeling towards the response variable on a continuous sliding scale (Mackerron, 2011). Additional questions are also trialled. Finally Subsection 7.1.3 builds on the results from 7.1.2 and describes the development of FOCAApp in a way that details each step of application development and functionality to create a reproducible structure.

7.1.1 Putting fear of crime (experience) on the map

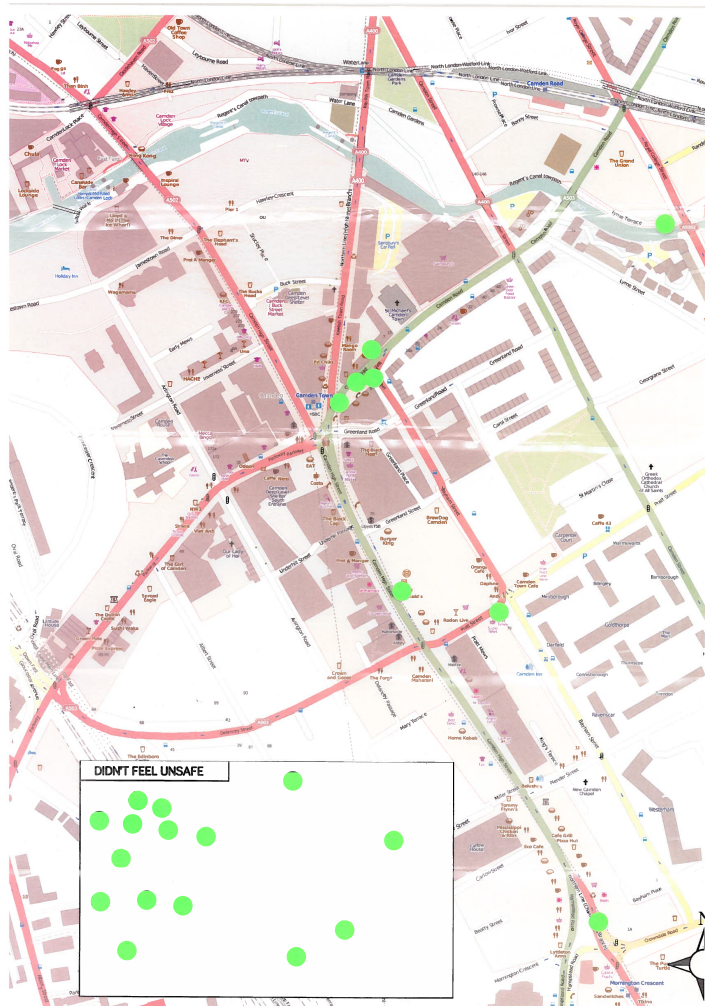
To design an application for recording spatial and temporal information about people's experiences with fear of crime, the first step is to determine whether something so subjective, that has often been described as an emotion or cognition can even be assigned specific point-level location and time stamp. Previous studies aimed at putting fear into a geographical map, (detailed in Chapter 2, Subsection 2.2.4) link people's experiences to their place of residence, or general neighbourhoods of familiarity. Other approaches include cognitive mapping of avoidance behaviour (asking people to point out on a map general areas where they avoid due to fear of crime (Doran and Burgess, 2012)), asking people about their feeling of safety in one particular spot on a university campus (Fisher and Nasar, 1992b), or following them along a route through a university campus, asking them to narrate their levels of fear (Nasar and Jones). While all three studies move towards attributing spatial information to people's perception of safety, none of them pinpoint specific instances of worry. Rather, they continue to tap into general anxieties, and create the spatial information either by asking people to recall their general attitudes and anxieties (as in the case of cognitive mapping in Doran and Burgess (2012)) or create the spatial information artificially in advance, by selecting a particular route or study site, and asking participants to evaluate these after the fact (Fisher and Nasar, 1992b; Nasar and Jones). From this previous work, it is not known whether people do experience fear of crime events in a way that they can link it with a specific time and place. In order to be able to measure fear of crime at this resolution, it has to be determined whether people are able to provide such perceptual time

stamp information at all. Perhaps the reason no one has asked about fear of crime in this way is that it is not how people experience this.

To examine whether people can attribute point-level spatial information to their fear of crime events, a small-scale participatory mapping exercise was carried out along a small section of the London borough of Camden. The approach taken was to present participants with a printed Open Street Map GIS map, and ask them: 'have you felt worried about crime in past 3 months?'. Participants were also given a sticker. If they answered 'No', they had not felt fearful in the last 3 months, they were asked to put the sticker in the empty box provided at the bottom of the map. If they answered 'Yes', they were then asked 'would you be able to put this sticker on the map to show where you felt unsafe?'.

This method of participatory mapping was chosen for this pilot as it is a successful method of quickly and efficiently collecting participatory geographical information (Vajjhala, 2005). Participants were recruited by being approached for on-site interviews by the interviewer (me) walking around the site and approaching people asking them to participate, similar to the sampling methodology of Fisher and Nasar (1992b) when measuring perception of safety in various locations at a University Campus. Except rather than asking about the location of the interview, participants were asked to refer to any location, within the scope of the map. People were approached for the duration of one hour of survey activity, and overall 23 participants were reached. Most people who were approached agreed to participate. Those who refused were not recorded. All people who refused gave the reason of not having enough time to stop and participate. The majority of the people interviewed have not felt unsafe in the past 3 months (15 people), but those who have were all able to locate the specific event on the map (Figure 7.1). Interestingly, none of the participants referred to the area as a whole, but instead each response was about a specific fear of crime event, triggered by something people saw or experienced.

This short experiment served to affirm that it is possible for people to assign a location to a fear of crime experience, and it would, therefore, be possible to collect spatial information about these fear of crime events. This approach

Figure 7.1: Sticker map from participatory mapping of fear or crime exercise

to participatory mapping of fear of crime, by presenting people with a map and asking for the past 3 months, is another way of creating maps of people's experiences with fear of crime. However, it is restricted to the area covered in the printed GIS map, and any collection of temporal information about when the experience occurred would rely on participants' ability to recall this information. Instead, the aim of this research is to make use of advances in spatial technology and incorporate the methodology of ESM described in Chapter 3, Section 3.4, to be able to map fear of crime as and when people experience it in their everyday lives. As such, while participatory mapping in this sense is a good way to collect spatial data, it remains cross-sectional as it ignores temporal fluctuations. Instead, in order to be able to record fluctuations in fear of crime within people over place and time, it would be ideal to apply ESM and

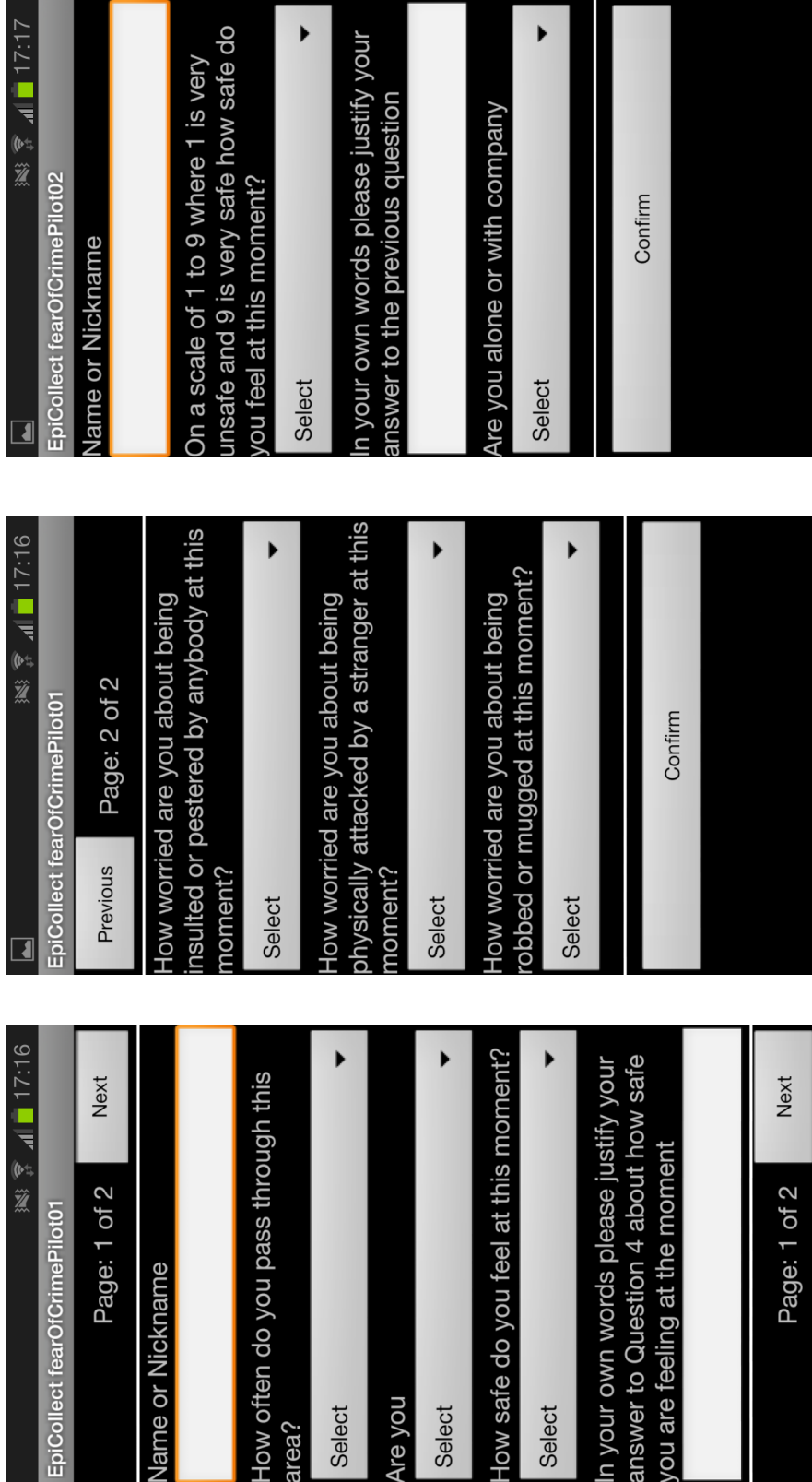
participatory mapping to a mobile application, for surveying people about their perception of safety as they go about their everyday routine activities.

7.1.2 Questionnaire development

To move towards developing an ESM application for measuring fear of crime, for the very first digital pilot of the study, the online survey-building application EpiCollect was used (Aanensen et al.) to create two separate questionnaires. EpiCollect was discussed briefly as a survey tool in Chapter 3, Section 3.4. To review, it is a free-to-use mobile application that allows researchers to create and deploy custom questionnaires to anyone with the EpiCollect application installed on their mobile phone. One questionnaire would take the approach of using the questions about fear of crime from the Crime Survey for England and Wales (CSEW) (formerly British Crime Survey). In the CSEW, the question: 'How worried are you about....?' is repeated for various crime types (Office for National Statistics, 2014). For this pilot, the questions were only asked for three selected crime types: 'Being insulted or pestered by a stranger', 'Being physically attacked by a stranger', and 'Being robbed or mugged' (see Figure 7.2b). Besides the questions about fear of crime, demographic questions were also included, asking people about their familiarity with the area, their gender, a general evaluation of their feeling of safety in that moment, and a free-text option where they could mention anything that made them feel worried (Figure 7.2a).

The second questionnaire took a different approach and instead asked participants to rate their feeling of safety in that moment from 1 to 9, and then use a free-text field to justify their answer. Further, it asked whether the person was alone or with company (Figure 7.2c).

Both forms had to ask participants to enter a unique name or nickname so that repeated answers from the same person could be linked. Further, both surveys also collected coordinates from the GPS of the mobile device, and the time stamp when the survey was submitted. A group of 5 University College London (UCL) Engineering students were asked to trial both versions of the survey, in two rounds of guided walks around the university campus, and stop-



(a) EpiCollect pilot 1 page 1

(b) EpiCollect pilot 1 page 2

(c) EpiCollect pilot 2

Figure 7.2: Piloting app questions using EpiCollect

ping at pre-selected locations to complete the questionnaire. The questionnaire based on the CSEW questions (modified to change the scope from 'In the past 12 months' to 'In this moment') was trialled first, followed by the second questionnaire with rating safety on a numeric scale. After the walkabout, the pilot participants were invited to a focus group meeting to discuss their experience. The discussion covered their own experience, as well as what they thought that future challenges could be.

Three main issues emerged from the discussion. The first was that the questionnaire using the CSEW questions was tedious to complete multiple times, due to the repeated questions with the different crime types. Since all the different crime types were listed each time the participants completed the application, if they felt worried about one thing, they would have to write down what they were worried about, but then they would also have to answer 'Not at all worried' to all the other crime types, before being able to submit the report. Pilot participants found this repetitive, and assumed it might discourage future participants from continuing in the study for longer amounts of time. However, they preferred the wording of the questions from the CSEW in terms of responding, as opposed to the second questionnaire which asked them to rate their safety on a numeric scale of 1 to 9. As a result, a decision was made to use the CSEW question and answer wording, but to not repeat this for each crime type. Instead, if a participant answered that they were very or fairly worried, a list of the possible crime types (all taken from the CSEW, but modified to make clear that I was asking about the current place and time) would be presented to them, to then choose to indicate *what* they were worried about. This also allowed for measuring fear of more types of crime than just the three pre-selected ones, without increasing the workload for participants.

The second issue which emerged was to do with the possible danger of someone putting themselves or their property at risk by being required to complete the questionnaire at a time when they felt unsafe. Or if they reported it later, after having moved to a safe place, the GPS location sent by the mobile phone with the report could be incorrect. If someone felt unsafe on their journey home, they would not be inclined to stop, report it, and then continue,

instead, they would want to get home as soon as possible, put themselves out of harms way, and report it later. In order for participants to be able to do this, there needed to be a way for them to enter the location of the incident to link to the report, as well as the time of the incident, rather than always sending their current location and the current time. As a result of this, a decision was made to include a retrospective annotation option, where participants can use a map to assign a location to their report, rather than always have to rely on their current location. This allows people to prioritise removing themselves from a dangerous situation first, but still be able to report about this location later, with accurate spatial and temporal data attached.

The third issue was similar to the first one of the repetitiveness of the questions, but in addition to causing participants to become frustrated and potentially increasing attrition rates in a longitudinal study, this issue can cause problems even if participants are willing to repeatedly participate. This issue was with asking people to enter their name or nickname repeatedly manually. By allowing non-validated entry of a unique identifier by participants, it becomes possible that multiple people pick the same name (for example if two people named 'Nick' participate, they might both choose 'Nick' as their username), and this was not controlled for by Epicollect at the time of this trial. Further, since people have to type in their username repeatedly, typos become possible, resulting in multiple reports from the same person being counted as coming from two different people. To avoid this, a decision was made to use the phone or an existing account on the phone to automatically assign a unique user ID for each participant. This ID can then be used to link all reports to the same participant. As it is automatically assigned, there is no change for typos or other user error, and as it is based on a user ID previously created with a client which uses validation, the identifier is certain to be unique as well.

After the focus group, an initial look at the data also resulted in some changes made for the purposes of the analysis. While the focus group revealed that repeatedly filling out the same question with the same answers becomes annoying for participants, looking into the possible analyses that I would like to carry out with the data, it became evident that I would like to collect things like

demographic information about the participants. Therefore, since the unique ID would be able to link reports together, a decision was made to create a separate database with the unique ID and the demographic questions, from which the reports can later be linked back to the demographic information. This would allow the participant to complete these questions only once, but using the unique ID, this info can be linked back to all related reports of fear of crime made by that specific participant.

Finally, the free text fields were deemed to not provide much additional value, and it emerged from the focus group that people felt obligated to fill them out, which resulted in them feeling like the questionnaire took more effort than they would be willing to give to it repeatedly over the course of a longer study period. Since this overall is an initial feasibility study of using such an app to collect spatial and temporal information about experiencing fear of crime, the qualitative detail coming from such free-text boxes was left for future iterations of the application.

Based on the findings from these pilot studies, it was decided that a bespoke mobile application would have to be built, incorporating the question from the CSEW. However, the question needed to be altered to reflect that the participants should respond about their feelings in the current time, and to ensure participants avoid having to complete it multiple times for all crime types. Further, this application would incorporate the mapping methodology from the participatory sticker mapping exercise in Subsection 7.1.1, to provide participants with an option to report something they had experienced retrospectively.

7.2 Building the Fear of Crime Application

The fear of crime application (FOCApp) was developed in Java programming language, for use on Android mobile devices. It was written and tested by the author and is not based on code from any other mobile application. It was created using the Android Software Development Kit in the Integrated Development Environment, Eclipse. It was designed to be simple, efficient, usable, and to be able to call built-in applications, such as the GPS sensor, using intents, in order to fully make use of the capabilities of the mobile phones that people

carry with them during their everyday lives. Learning how to do this eliminates the need for using separate GPS trackers and paper surveys or diaries that users may forget at home or find taxing to wear or use. The basic functions of the application are to allow individuals to submit reports of fear of crime events they experience, as well as to respond to questionnaires linked to the signal-contingent protocol 'pings' or reminders they receive. This section will describe in detail the application functionality and development.

The main fear of crime question was changed from the CSEW question to ask "In this moment, how worried are you about becoming a victim of crime?", allowing participants to select crime type later, hoping that the situation which they were in will give them context, instead of us having to prescribe it in advance. Participants were presented with 4 options to select:

- Not at all worried
- Not very worried
- Fairly worried
- Very worried

which are all taken verbatim from options from the CSEW questionnaire. Additionally, "In this moment" was added to the beginning of the question, to further emphasise that people were being asked to report about their current state, at the time of using the application. To describe how the application was made to accomplish this task, a step-by-step description of its use will now follow.

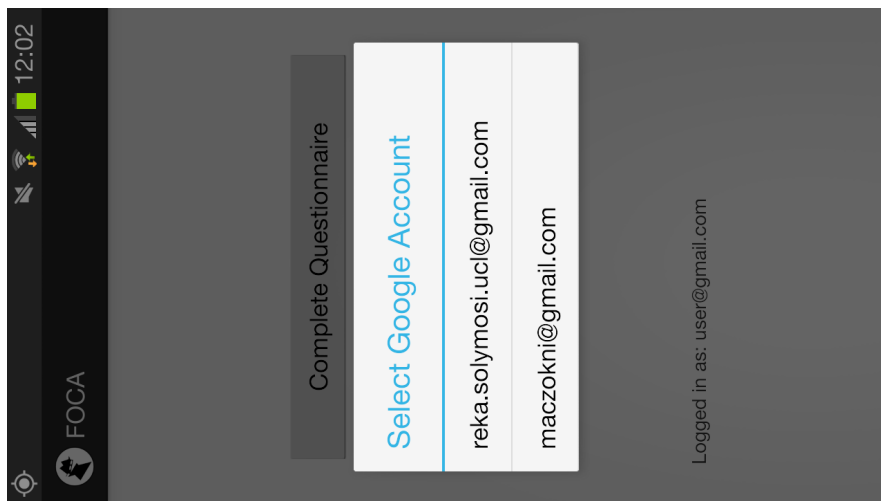
Upon opening the application, users are prompted to identify themselves using a unique Google login (Figure 7.3a). The application identifies and presents logins associated with the device to the user, making it easy for users to log in. While data is later anonymised, the use of an identifiable login is used to encourage honest reporting; fraudulent responding is an area of concern for online-based questionnaires, and it is recommended to use a means of personal identification to control for this (Lefever et al.). Once the username is chosen, it is checked in a database to ensure that participants have completed

a pre-experiment questionnaire, which they can fill out by visiting a website where they find the online questionnaire, asking about demographic variables.

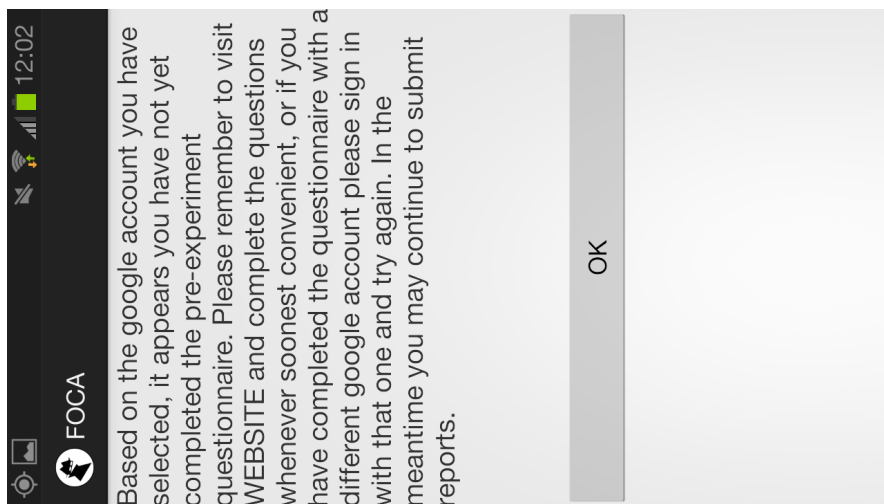
In case they have not yet completed the pre-experiment questionnaire, they are reminded to do so (Figure 7.3b). The reminder page also presents them with a link where they can easily complete the questionnaire immediately. If they choose to do this, they are presented with the demographic questionnaire. The application first asks 'What is your gender' and then 'What is your age?'. Gender can be selected from a drop-down menu, while age is free text input. However there are checks in place to ensure that the person enters a valid integer as their age (Figure 7.4). Then they are asked to select the cultural background they identify with from a drop-down menu again, containing a list of ethnicities provided in the CSEW. Then a general question about fear of crime, again taken from the CSEW is asked; 'Thinking about all types of crime, in general how worried are you about being a victim of crime?'. Participants can choose from the same four response types listed above. Finally participants are asked to provide their home postcode sector (the first half of their postcode) and work postcode sector, in order to help identify their area of familiarity. Finally, previous victimisation is assessed with the question 'In the last 12 months, have you PERSONALLY (not others in your household) been a victim of crime? Please include anything that happened to you at home, in the street, at work, in a shop, in a part, on a train, or anywhere else'. This question wording was taken from the CSEW as well.

If they do not have time to do so, but would like to submit a report, they may do so anyway and proceed by clicking 'OK'. After login, users are taken to the homepage (Figure 7.3c) where they can select one of three options.

The application is designed so that users can send three types of reports. The first type of report, sent by choosing the option 'Complete Questionnaire', corresponds to a signal-contingent protocol of the experience sampling method, where participants are sent a reminder (ping) to complete the fear of crime questionnaire at that time. As early as 1985, 'beeper technology' was being used to signal to participants a request for them to record their experiences while going about their days (Pervin, 1985). This method is most suited for



(a) Log in page of FOCAApp

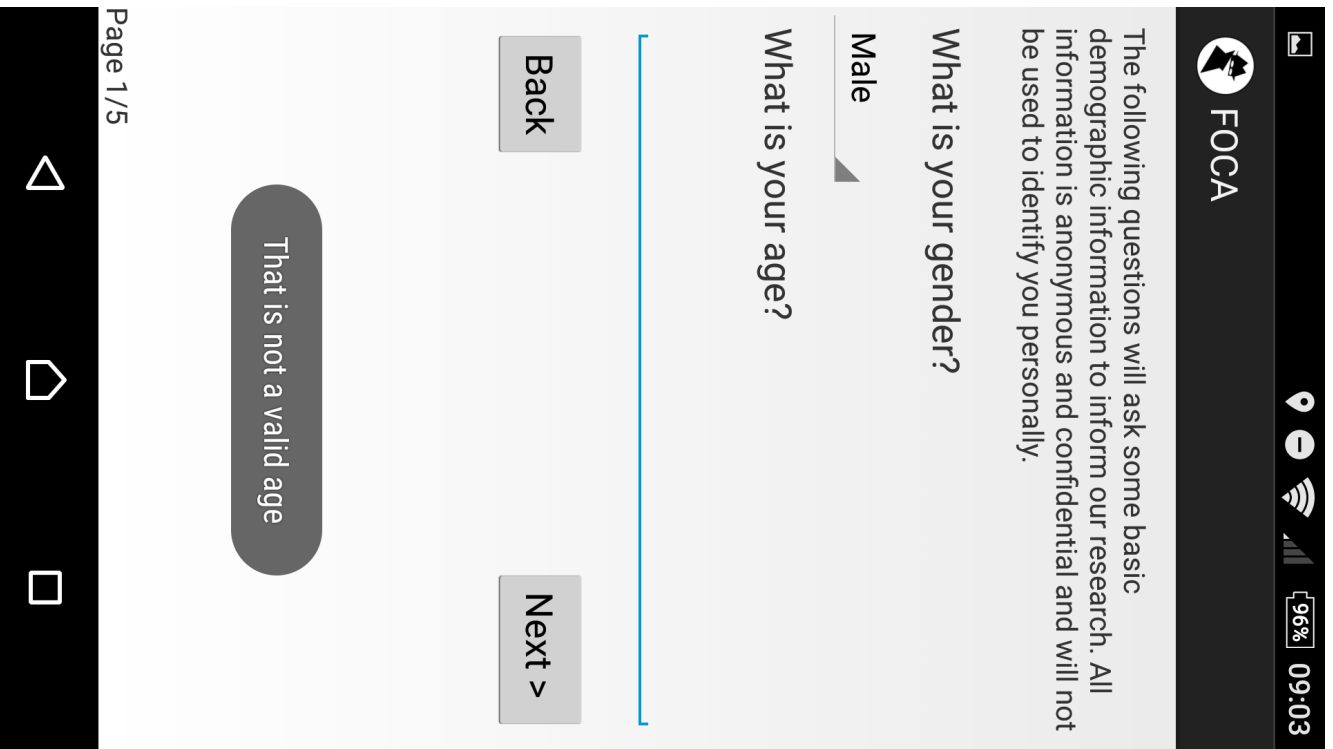


(b) Reminder to complete pre-experiment questionnaire

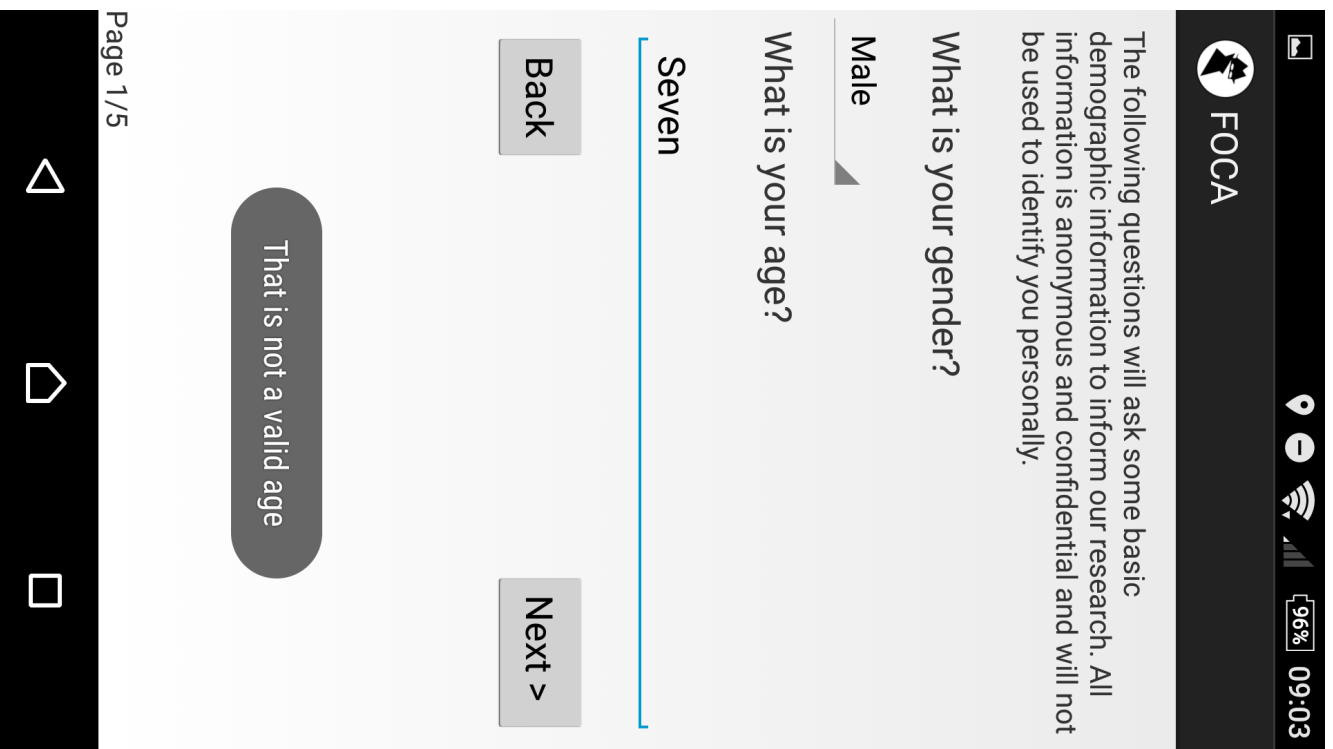


(c) Home screen of FOCAApp

Figure 7.3: FOCAApp initial screenshots



(a) Attempting progress leaving age field blank



(b) Attempting to progress with non integer age entered

Figure 7.4: Validity checks on free text responses

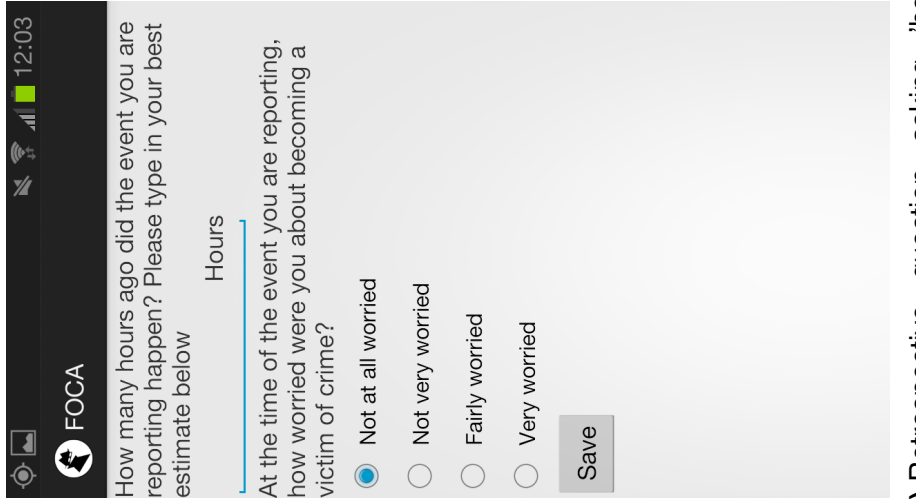
projects that measure on-going behaviours, susceptible to retrospective memory bias and to cognitive or emotional regulation. Fear of crime fits these criteria, and by applying this method to examine whether fear of crime is present as an ongoing phenomenon, it is possible to avoid bias resulting from emotive and cognitive regulation or problems with information recall. To carry out this type of experience sampling, there are traditionally two required instruments; one is a signalling device that emits the ping according to a pre-determined schedule, and the other is an experience-sampling form (ESF) where the participant records information on the momentary situation and psychological state (Csikszentmihalyi and Larson). This is often a short answer questionnaire with mostly quantitative questions. This method is useful to ensure that enough responses are submitted during the course of this study. The innovation of FO-CApp, and the few similar apps out there is to combine these two tools into the one mobile application, that can be used both to ping people, and be the device on which the questionnaire is completed.

The second option, 'Report something now', allows participants to report a fear of crime event they might have experienced at a time when they did not receive a signal prompting them to send a report (Figure 7.5a). This option incorporates an event-contingent protocol of experience sampling. This method involves reporting an experience immediately or closely following the event of interest (Csikszentmihalyi and Hunter). In this case, the experience of interest is an experience of fear of crime. Since the goal is to measure instances of fear of crime as they are experienced in everyday life, the opportunity for people to report something as it happens is necessary. An issue with asking people to report fear of crime events using smartphones is the possible danger into which participants may put themselves or their valuables. When experiencing a fear of crime event, a participant may not be inclined to make their valuable mobile device visible and vulnerable. To account for this, retrospective annotation was chosen as a third option to send a report. Found under 'Report a Previous Incident', this option allows users to choose the location they want to report about on a map, saving the coordinates from their touching the screen at the location in question (Figure 7.5b), rather than using the GPS, allowing them to remove

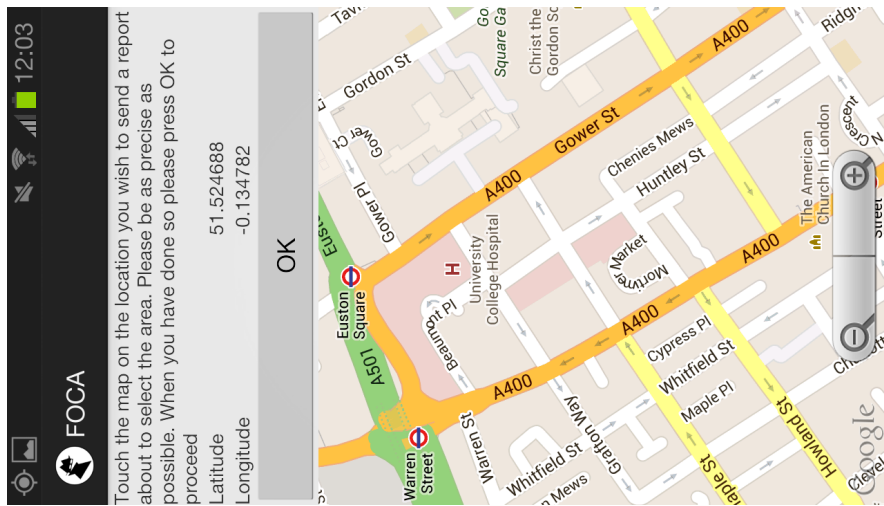
themselves from the situation, and still send accurate geographical information. The questionnaire then asks how long ago the incident took place (in hours, as users are asked to report any fear of crime events that they experience as soon as possible afterwards, once they feel comfortable doing so), to also gain an accurate time stamp of the event. After providing this supplementary information, the user then answers the same survey questions (Figure 7.5c). Retrospective annotation was introduced as an option so participants do not feel pressured to use their potentially very valuable phone in a situation where they may feel unsafe, but still be able to report this situation.

Finally, if a participant answers 'Fairly worried' or 'Very worried' about the main fear of crime question, an additional window appears, asking an additional question to record what crime type it was that they felt worried about. These crime types are again taken from questions in the CSEW (Figure 7.6), to allow comparability.

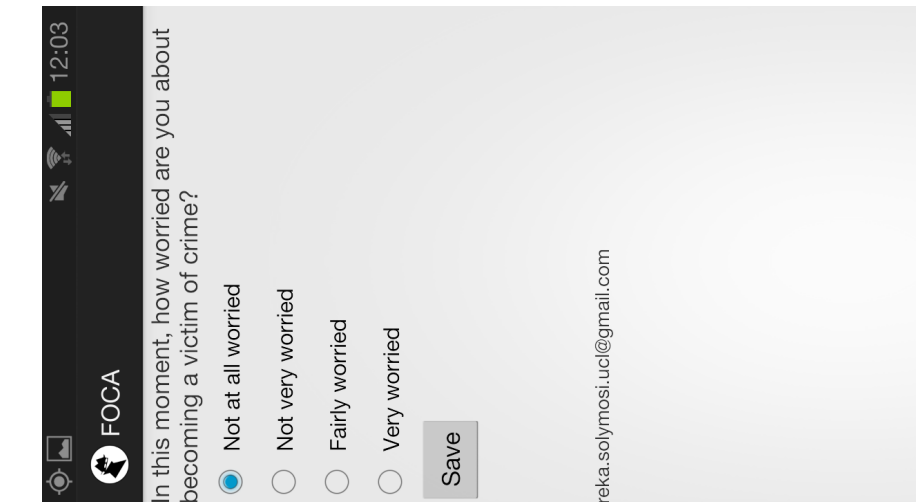
After a questionnaire is completed, a participant sends his or her response by pressing the 'send' button. Data is then sent over an internet connection to a secure, password protected university server, where it is then stored in a MySQL database to which only the researcher has access. Data can be downloaded in table format, saving time on having to enter ESM data manually, which can take significant time resources traditionally (Mackerron, 2011). A flowchart illustrating this whole process of the FOCA application can be seen in Figure 7.7



(a) Fear of crime question in FOCAApp



(b) Retrospective annotation option to select location on map



(c) Retrospective question asking 'how many hours ago' as well as fear of crime question

Figure 7.5: FOCAApp main page screenshots

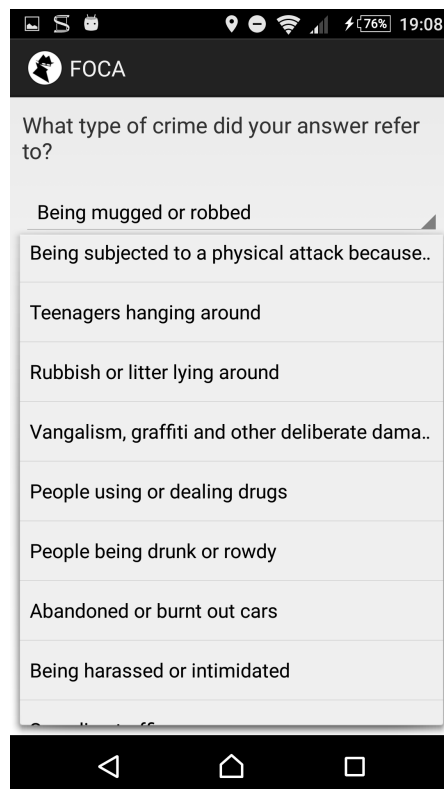
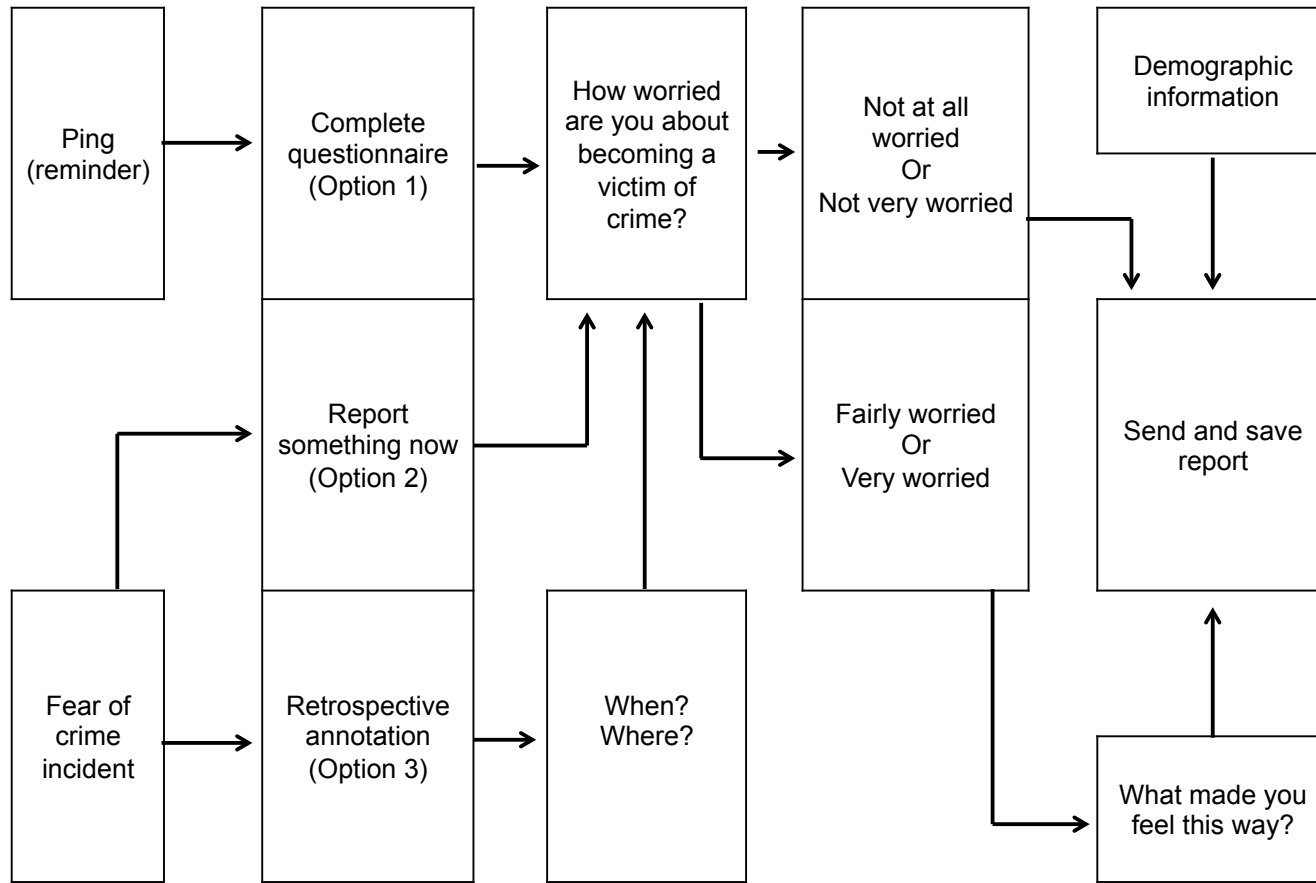
Figure 7.6: Final page of application presenting choices for reason for fear of crime

Figure 7.7: Flow chart illustrating process of FOCApp



The data collected includes username (Name), date and time (Time), GPS coordinates (Location), an identifier of which question type they answered (ID), and the responses to the questionnaire (Q1, Q2, and Q3). If the report was sent using retrospective annotation, the time stamp also includes the additional information of how many hours ago the event being reported took place in the format 'YYYYMMDD/HHMMSS-hours ago'.

7.3 Initial changes and application testing

7.3.1 Changes to ensure spatial and temporal accuracy

Before running a full-scale pilot of the FOCAApp study, a feasibility trial was conducted to test the application. Only option one, the 'Complete Questionnaire' option was used. The main aim of the feasibility study was to assess the functionality of the application, and the ease or difficulty with which participants would be able to use it and understand it. I had a total of six participants who submitted a total of 39 data points for this experiment. Reports submitted were sent immediately over a network connection to a web page written in PHP and stored in a MySQL database on the UCL geospatial webserver. The 39 data points were mapped using a simple point map to give an indication of what data would look like, and what changes in recording would need to be made to the application.

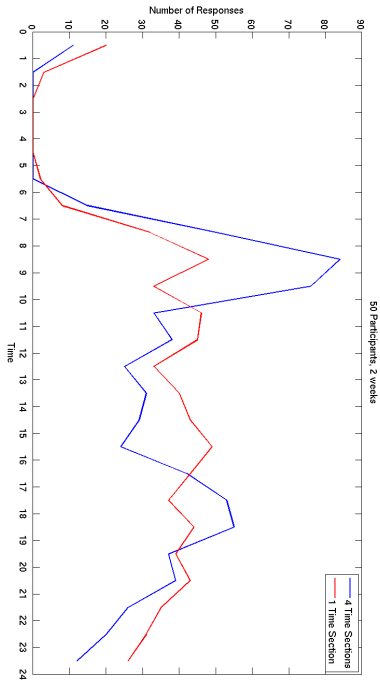
To determine the best approach for sending out reminder pings for the signal-contingent protocol of the experience sampling to ensure equal coverage of different times of day (as routine activities change with different times), two ways of administering the notifications were considered. One method distributed the time of pings randomly throughout the day, and the other broke the day up into different times, according to differences in activity patterns, and used a stratified random sampling of times. This option required the segmentation of the day into four time slots, based on peak travel times as identified by Transport for London: Morning commute (6:30 - 9:30 hours), daytime (9:31 - 15:59 hours), evening commute (16:00 - 19:00 hours), and night-time (19:01 - 6:29 hours), as these all represent prevalence of different types of routine

activities.

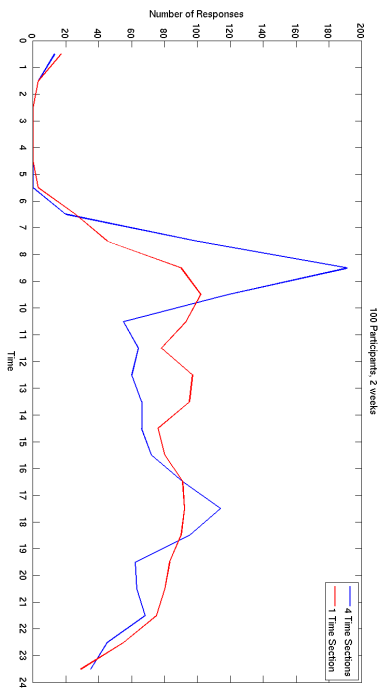
To choose between the two methods, a large-scale simulation of hypothetical pings with each method was performed, to see what sort of distribution of time samples would return with each one. In line with signal-contingent protocol ESM best practice, participants are allowed to choose a start and end time in the day during which they are happy to receive pings, in order to avoid bothering them at inconvenient times (Delespaul, 1992). In order to account for variation between participants' preferences, each simulated individual was randomly assigned a preferred start time between 5:30 and 8:30 hours at the earliest, and an end time between 21:00 and 2:00 hours at the latest. It was also assumed that at every ping, a data point would immediately be submitted for the purpose of this simulation.

Four scenarios were simulated, all of them assuming that participants would be pinged four times a day, and would respond to each ping immediately. The scenarios were: having 50 participants over 2 weeks, 100 participants over 2 weeks, 50 participants over 4 weeks, and 100 participants over 4 weeks. Results suggested that random pings throughout the day show an equal distribution of responses over the course of the day, but fewer during the morning commuting hours. Figures 7.8a, 7.8b, 7.9a, and 7.9b show an example of simulated number of pings distributed over time using both methods for each scenario, where the blue line is the scenario with the day stratified into the four sections detailed above, and the red line is the day as a whole. The stratified approach of splitting the day into four segments returned a better coverage of all times of day, therefore a decision was made to use stratified random sampling, as it represented times of movement more effectively.

The day was therefore split into the four sections, and a random number generator was used to pick times within each time slot for 'pings' to be sent out to participants. A random number generator was used because according to ESM best practice, the reminders should be sent at non-regular intervals, in order to provide a representative insight into participants' experiences over time. It also serves to eliminate issues with participants anticipating the questionnaire near a regular sampling time, and changing their behaviour, or the

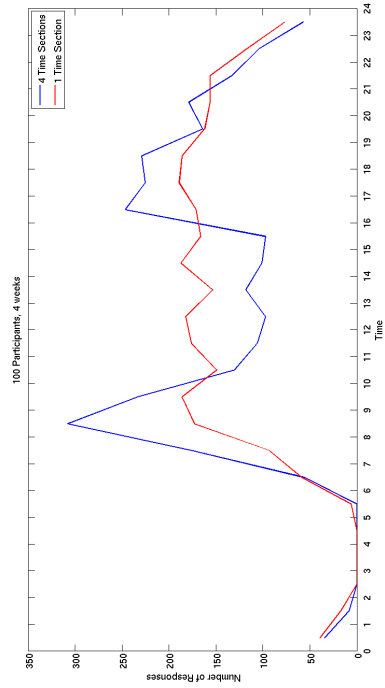


(a) Simulation of 50 participants over 2 weeks

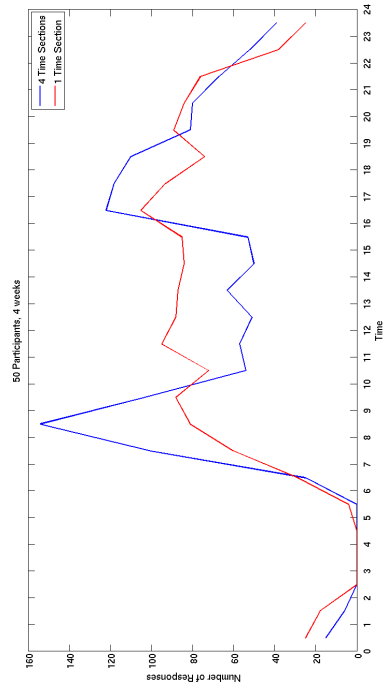


(b) Simulation of 100 participants over 2 week period

Figure 7.8: Simulations of participants over 2 week period



(b) Simulation of 100 participants over 4 weeks



(a) Simulation of 50 participants over 4 weeks

Figure 7.9: Simulations of participants over 4 week period

sampling taking place always at the time of some regular activity (?). Participants were able to select a number of times they were willing to be pinged per day (between 1 and 4, in line with best practice recommendations for ESM research (Delespaul, 1992)), and were sent reminders accordingly. The delay between pings and response was not considered, as the aim is to collect data on people's experiences at the moment of recording, regardless of the proximity of recording to the original ping. This policy is easiest for participants and does not risk introducing the biases that ESM is designed to eliminate (?). Therefore the decision was made that the reminder should be non-intrusive, and therefore was not accompanied by sound or haptic notification, instead it was delivered in the form of the FOCApp logo appearing in the user's notification bar, with a text asking the participant to complete the questionnaire at the soonest convenient time. Tapping the notification opens up the app to the 'Complete questionnaire now' page of the application, to ensure it was as simple as possible for participants to respond to the ping.

The final question left to address was the spatial accuracy of the data collected by the smartphones. This initial form of the application used a method that would call 'last known location' of the phone. This means that if no immediate GPS signal was found, the cached location would be used. This cached location calling method provides a fast location fix when the time it takes for the phone application's location listener to receive the first location fix is too long for the user to wait for (Android, 2013). While in regards to the usability of the application this implementation is recommended, in terms of the collection of accurate spatial information about fear of crime events, the feasibility study found that this method resulted in multiple false locations sent with reports. For example, a report sent from the main UCL campus would still show up as being sent from Euston Station (which is 0.3 miles or a 7 minute walk away), as that is where the user first received signal after their commute, and location had not been updated since. Such an error margin is too high to accept if the aim of the study is to map micro-level variation in fear of crime.

To remedy this, the application code was changed to encourage the user to wait for a fresh GPS signal to send an accurate location to the application, and

only allows the submission of a FOCAApp report after this has occurred. While the time delay associated with this might cause the user to abandon making a report, it was deemed better to not receive a report than to receive a false report where the location of the event was untrue. The retrospective reporting option remained open to participants, and they could submit a report by finding their current location on the retrospective reporting map, and enter "0" when asked how many hours ago the event took place, in order to still submit a report, when their GPS signal was not found. As a result, the spatial accuracy of the data can be relied upon, with minimal accuracy issues. In general GPS location tools are fairly reliable but caution must be exercised in labelling these as infallible. There is evidence for example that a major limitation to GPS is the inability for receivers to determine their position indoors, underground, under dense tree coverage, between large buildings in urban canyons, and anywhere else where a solid object obstructs the view of the sky (Zandbergen and Barbeau, 2011).

7.3.2 Pilot testing the application

As mentioned, the initial exploration of the feasibility of FOCAApp, six people (from a university setting) were asked to download and use it for the duration of just over 1 month. One aim of the pilot was to ensure maximum spatial and temporal accuracy of the data collected, as discussed in Subsection 7.3.1. Another aim was to determine the extent to which the application was usable as intended, and measured what it was intended to measure. This section serves to assess whether participants were using the application in the way that was assumed, and whether the data collected by this application would be sufficient to answer the research questions (Subsection 7.3.1), and also whether it accurately reflected participants' experience with fear of crime as something they experienced as part of their everyday lives (Subsection 7.3.2).

7.3.2.1 Process validity

Firstly, the participants' use of the application, and whether that was in line with what was expected (as outlined in Section 7.2) was assessed. The majority of responses were submitted as a response to a ping notification; 76 % of reports were submitted after the participant clicked on the notification, and

only 24% were made independently using the 'Report something now' or 'Report a previous incident' options. This was in line with expectations since fear of crime is something that is a relatively rare event, people will not often encounter something that will make them experience fear, so to collect regular data about people's levels of fear of crime, they will need to be pinged periodically. However looking into the distribution of the responses shows that people reported being 'Not at all worried' with the retrospective annotation option, and reports of worry were made after pings as well. Thus people's use of the reporting options was not necessarily as clear cut as initially assumed. Interestingly, of the reports sent using retrospective reporting, the majority (91%) were 'Not at all worried', suggesting that people were using this option to report safe areas or perhaps make up a missed notification, or using it to get around the phone not finding a GPS signal, rather than to report fear of crime events.

Delays in reporting the event using the retrospective report were mostly less than an hour (92%), which further supports the assumption that people were using this option to report about their current state using the map to select a location, to get around the phone not finding a GPS signal. The remaining retrospective reports were mostly made 1 hour after experiencing the event (3%). Only 2% were made after 3 hours delay or longer.

Initial results also demonstrate that the method succeeds in capturing within-person variation in fear of crime. By linking multiple reports with the unique IDs, the data format can demonstrate that the same person moves in and out of different levels of fear of crime and that this methodology of measurement is capable of capturing this information. While most of the time participants did not worry about crime, there were specific instances when fear was reported, illustrating longitudinal within-person variation in fear of crime, supporting an approach to fear of crime as a dynamic experience.

Further, the GPS data captures permit the examination of spatial characteristics. The point-level granularity of measurement also appears justified, as participants did not perceive an entire neighbourhood as safe or unsafe as a whole. The data shows different levels of fear of crime reported *within* neighbourhoods, as people reported certain parts at certain times as safe, and

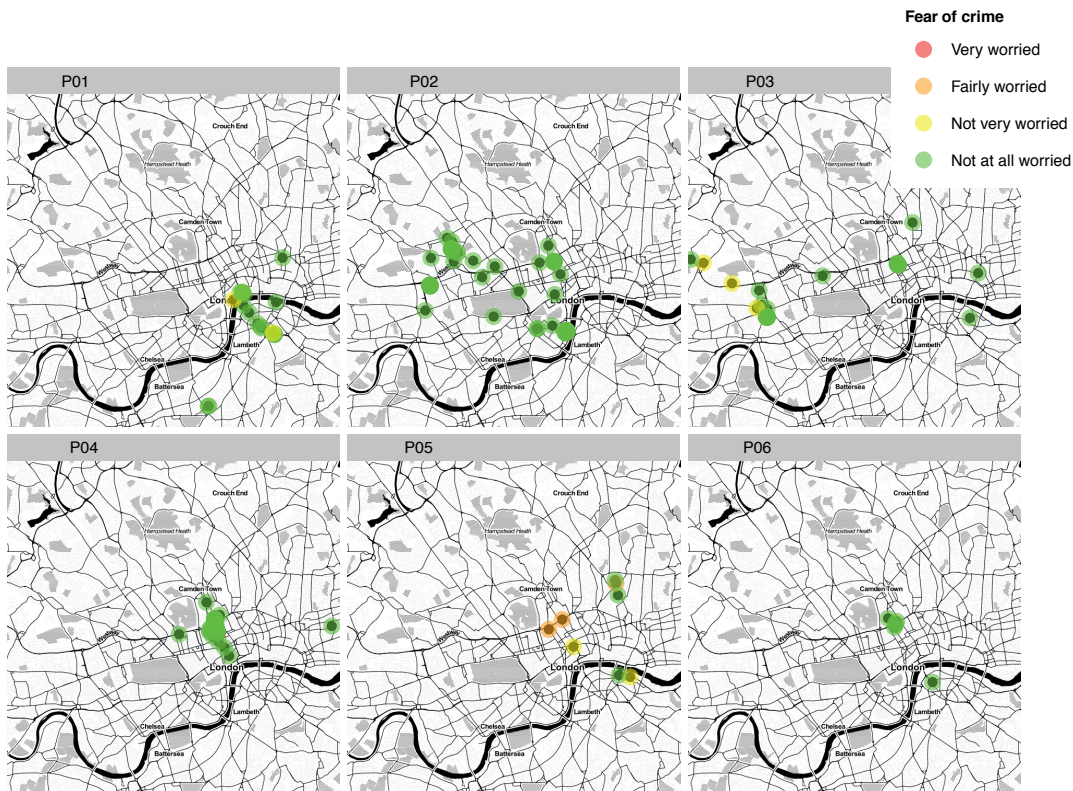
others as less so. For example, Figure 7.10 demonstrates micro-level geographical variation in the fear reports of one participant. The data also allow for exploration of inter-personal variation; Figure 7.11 demonstrates fear of crime fluctuations for all six participants for the same geographical area. This further affirms that data collected using this tool could be used for spatial mapping of fear to explore the potential existence of common 'hot spots'.

Figure 7.10: Fear of crime map for one participant



7.3.2.2 Measurement validity

To determine the validity of results as a reflection of the participants' actual experiences, short interviews were conducted with each participant, where participants were shown maps of their fear points, and asked to discuss whether that reflected their experiences in the past month. Usability and experience with the application were also assessed. Overall, participants found the application

Figure 7.11: Fear of crime map for 6 participants

straightforward and easy to use.

Issues with the application related to delays in phones' abilities to find GPS. The hypothesis that people used the retrospective reporting option to get around this GPS issue was further confirmed by these interviews. Multiple participants claimed that they used the retrospective reporting option, which was enabled to use even when a GPS signal was not found by the phone, in order to make a report about their current state, in response to a ping. While they all noted the delay caused by waiting for GPS to find a signal, no participant reported not submitting a report due to this; instead, they opted to use the retrospective reporting workaround or to wait until the phone found a signal. However, since these were pilot participants who were involved with the testing of the application, it is possible that they were more dedicated, and that less engaged participants in the future might not be so persevering. However as mentioned in Subsection 7.3.1, a decision was made during the design process that it is most important to ensure spatially accurate information, therefore a few lost reports due to user frustration were preferable over data points with

false locations from the phone's last known location point.

To evaluate the extent to which the data collected by this approach reflects people's experiences with fear of crime, during the interview, each participant was presented with a map of their reports and was asked a series of unstructured questions about their maps. All participants stated that their maps covered their activity spaces, including their home, place of work or study, and their travel in-between, as well as various other locations they had visited. However, one participant, who used a bicycle as her primary mode of travel, mentioned that she could not complete the survey during her commute, as it would have been unsafe while cycling, but not practical to stop.

Participants were asked to comment on the level of worry on their maps, and whether that accurately reflects their day-to-day experiences. All participants agreed that the map reflected their feelings of worry as part of their everyday lives. One person described it as follows:

Yes, I think so I think that I feel generally quite comfortable everywhere and in particular in the university where I'm in familiar surrounding surrounded by people I know or who I can identify with. Whereas at Euston there are slightly more unknowns because lots of people pass through there travelling or shopping or going to the cafe or whatever and it's a lot more transient and it's more difficult to spot things because there are a lot of people moving around.

It was also interesting to note that participants related fear reports to certain events which they believed were linked to crime, but not necessarily something that put the person themselves in direct danger. Below is one example of a participant's response to being asked to describe what happened when he indicated that he experienced being 'fairly worried' about crime:

I was on my way into university in the morning, and I was coming into Euston station and there was someone who looked like they were trying to remove a bike from the railings that had been locked in, and they didn't look like the owners of the bike. And then I suspected they were trying to steal the bike, so I reported my fear of crime because it was a specific incident of me seeing what I thought was criminal activity.

However, some responses were linked to direct experience; one participant

described an incident where someone on a bike attempted to snatch her phone. Luckily they failed to do so, and she could later report about this from a safe place. In this sense, the application records 'near misses' of crime as well as instances of worry.

Overall the pilot participants agreed that the results of the map reflected their experiences in the month in which they participated in the trial of the FO-CApp. Further in each case where a fear of crime incident was reported, people were able to recall something specific that made them feel that way, that was something taking place in the situational context. These findings reinforce not only that fear of crime may vary within a person in place and time, but also that this bespoke measurement tool is capable of capturing this dynamic variation, allowing for the collection of data about fear of crime as a dynamic everyday experience that is influenced by the situational context.

7.4 Ethics

It is very important to also address the ethics of this research, as it collects personal information from people, as well as spatial and temporal tags of their locations and whereabouts while asking them about a topic with an emotional tint to it. There are three main potential ethical concerns to consider:

1. Collecting location data
2. Putting participants in dangerous situations
3. Increasing fear of crime in participants by making it more salient in their minds.

Collecting spatial information about people's activity patterns can be a sensitive issue. This information could potentially be used to track people without their consent. By looking at the times and repeat locations, it is easy to work out where participants live, where they work, and where they spend their leisure time. This information is quite sensitive, especially when linked up with personal data. To ensure the safeguarding of this data, fear of crime reports with the spatial and temporal information were sent to a separate server than the de-

mographic information. The data was only linked up for the purpose of the analysis, after which it was de-coupled again. Ethics approval was sought by the university ethics committee, and several iterations of the application were considered, before it reached final form, and was accepted by the University Ethics Committee (UCL Research Ethics Committee Project ID Number: 3692/004). The key important messages were to only take spatial information when the user explicitly submitted this. While some applications might track people and get their location at some specific time interval, the FOCAApp took location information only when the participants submitted a report. Also, great care was taken to ensure that participants were aware that they are submitting their geographical location each time they completed the survey, and that they did not send any reports from areas where they did not want to be located to. Interviewees all noted that they understood that they were sending their locations with each report, and did not worry about being tracked at other times.

The second issue is with participants putting themselves in dangerous situations to provide data. This could take the form of participants visiting areas they perceive to be dangerous, or by participants having their valuable smartphones exposed in potentially vulnerable locations. To guard against these issues, participants were given detailed instructions during the briefing, that the study is interested in their routine activities, and so it is preferred that they do not deviate from the routes they normally take and do not behave in a way that is not in accordance with their usual patterns of activity. The following statement was also sent out with the application:

We would like to stress that you do not put yourself in vulnerable situations during the course of this study. We advise that if you experience a situation where you feel unsafe, you first remove yourself from the situation, and use the 'Report a previous incident' option once you are back in a safe place.

In the interviews, all participants confirmed that they had noted this message and that none of them visited new areas as a result of the study, but instead carried out their daily activities as normal. The participant who had almost had her phone snatched said that she was not using the application at the time, but was making a phone call, and did not use the application to report the

incident until later, from a safe place. From this pilot, it can be concluded that people did not put themselves or their phones in risky situations as a result of participation in the study.

The final issue discussed here has to do with increasing fear of crime in participants as a result of repeatedly asking them about it, increasing the salience of crime and potential victimisation in their minds. While the interviewees all denied feeling increased fear of crime as a result of participating in this survey, it is possible that they did not overtly realise this, or that they were hoping to not look worried in the eyes of the interviewer. However in order to measure fear of crime, a question must be asked, and it can be argued that other methods of asking people about fear of crime could also have similar effects. Overall, however, there was no steady increase in fear of crime reported over time in any of the pilot participants. This can be monitored in participants of the longer study, and if it appears that their fear levels increase with longer participation in the study, then perhaps the argument should be made against measuring fear of crime in this way, as it might have negative effects on the study participants.

7.5 Discussion

This chapter has proposed a new approach to studying fear of crime to support framing it as a dynamic and micro level experience, lived by people as they go about their routine activities. To support this approach, Section 7.1 and 7.2 described in detail how a new measurement tool was developed and tested, for the purpose of collecting empirical data about fear of crime as an experience, that also has spatial and temporal information. While small, the trial of the FOCApp described here suggests firmly that fear of crime is indeed a dynamic variable that changes within a person over place and time as well as between people. Any data collection procedure that does not recognise this is subject to averaging and aggregation bias and if enquiring about feelings too far in the past, many other forms of survey bias, as discussed in Chapter 3. Finally, Section 7.4 details some important ethical considerations that must be taken into account with the development of this new research approach.

Overall, initial indications from the data presented here suggest that reports of fear events were tied to specific situations (such as the witnessing of a potential bicycle theft), and most reports are of people feeling 'Not at all worried'. The next chapter will describe in greater detail the wealth of information about dynamic and small-scale variability in fear of crime experiences within people. By conducting a four-month study of a larger group of participants using the application, more detailed insight into dynamic, within-person fluctuation in fear of crime can be attained. There, limitations of this approach will be further detailed, along with lessons learned to inform future work hoping to adopt similar techniques, alongside an illustration, with data from the study, of the possible new insight that can be gained from an environmental approach to studying fear of crime.

Chapter 8

Fear of crime as a context-dependent experience

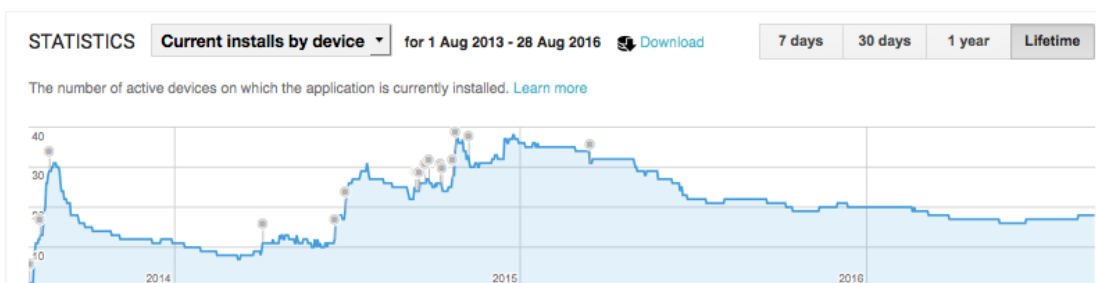
Chapter 7 provided a detailed outline of the development and validation of a research tool for the measurement of fear of crime as a dynamic, everyday experience. This chapter describes a four-month long study utilising this research tool. Emphasis on study deployment and lessons learned will hope to inform future work adopting similar techniques. Accordingly, Section 8.1 focuses on the study design, and Section 8.2 details the study sample. Section 8.3 presents descriptive findings of within-person variation in fear of crime, as people move across different activities. This will be discussed to give an illustration of the novel insight into fear of crime that can be attained by collecting information in this way. Section 8.4 then uses the new data collected with FOCAApp to identify situational co-variates of fear events. Then Section 8.5 outlines two examples, to illustrate the potential impact of adopting this methodology for the study and measurement of fear of crime. Finally Section 8.6 discusses the strengths, limitations, and impact of how the FOCAApp measurement tool is capable of recording fear of crime experiences in a way to demonstrate how fear varies within people with situational factors. It also serves to illustrate how this approach can be used to gain new insight into people's experience with fear of crime, and inform situational prevention measures aimed at reducing these fear experiences.

8.1 Study design

The design of this study is that of a longitudinal study, framed as an extended case study. It is a prospective rather than retrospective study, as participants' fear of crime is measured from the start of the study and throughout its duration. Further, a within-subject design was used as all participants were measured with the pre-experiment questionnaire and were asked to use FOCApp for the duration of the entire study, taking repeated measures from them while they participated.

Participants were recruited through the university's weekly newsletter, which contains a section that advertises studies looking for participants. Advertising of the study was also carried out using social media (Twitter and Facebook), posting in online forums, and flyering on the street near busy tube stations in the Camden area. To incentivise participants, a monthly draw for an Amazon gift card was advertised. Participants were told that the more reports they submitted, the more times their name would be entered in the draw, which was hoped to increase not only people signing up, but also to sustain participation, and ensure that people stay with the study over the long time of 4 months. Participant recruitment started 3 weeks prior to the start of the study, but recruitment waves continued during the study as well. Figure 8.1 shows the number of devices which had the application installed every day from its launch until time of writing, demonstrating that there were peaks of downloads (which correspond to pushes in recruitment) throughout the study duration.

Figure 8.1: FOCApp downloads from Google Play Statistics



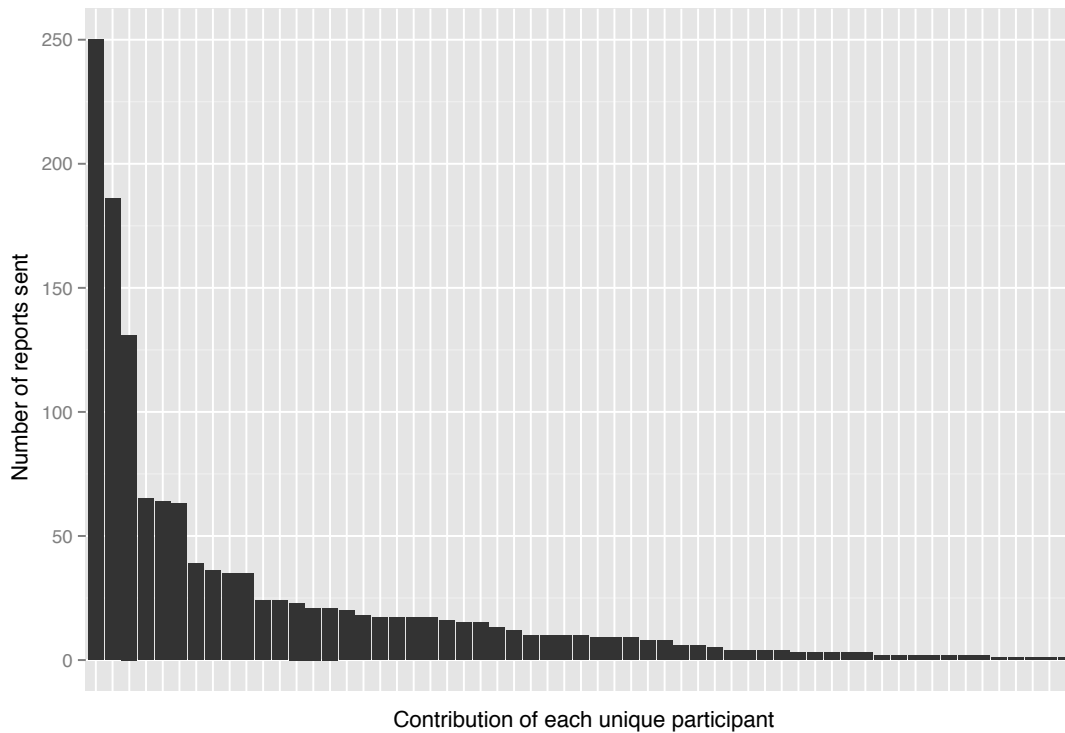
Instructions for participants were posted in the adverts, social media posts, and flyers. The instructions were also in the description of the application on

the Google Play store. Further a video was uploaded to YouTube which demonstrated how to use the application. Contact details about how to reach me were also provided, although very few participants made any contact at all. The study was to run for four months, while participants received automated reminders built into the application to report their feelings of safety. Once a month, I emailed all participants with a short message thanking them for their participation, and announcing the winner for the amazon gift card. I also occasionally tweeted updates about the study and some preliminary maps, but there was no way of checking if participants were following the Twitter account for the application, as participation was anonymous. However, they were made aware of it, and would have been able to access these updates. After the four months, data was saved and downloaded from the servers for analysis.

8.2 Study sample

Altogether, 59 people took part in the study over the four month period. In interpreting the trends it should be noted that this is not necessarily a representative sample of any particular population, as it was a self-selected sample of participants (Sterba and Foster, 2008), as anyone who downloaded the app could participate, and no one was excluded. The average age was 29 years, with the youngest participants at 19 years old, and the oldest participant at 56. Most participants were 35 or under (48 of the 59, totalling 81%), while only 6 participants were older than 35, and 5 did not provide their age. While the sample is definitely skewed to a younger population, on the whole London does have a higher proportion of the population under 35 than other UK cities, according to 2011 Census (Census Information Scheme, May 2015).

53% of the respondents were male, 34% were White British and 31% White Other. The remaining one-third of participants noted 'Caribbean', 'Chinese', 'Indian', and 'Other Asian background' as their ethnicity. According to the 2011 Census, the largest ethnic group of London's population is 'White British' (45%). The next largest population groups are 'Asian or Asian British' (18%), 'Black or African or Caribbean or Black British' (13%) and 'White Other' (13%) (Census Information Scheme, June 2013). It appears that in this sample people who

Figure 8.2: Reports sent by each participant over course of study

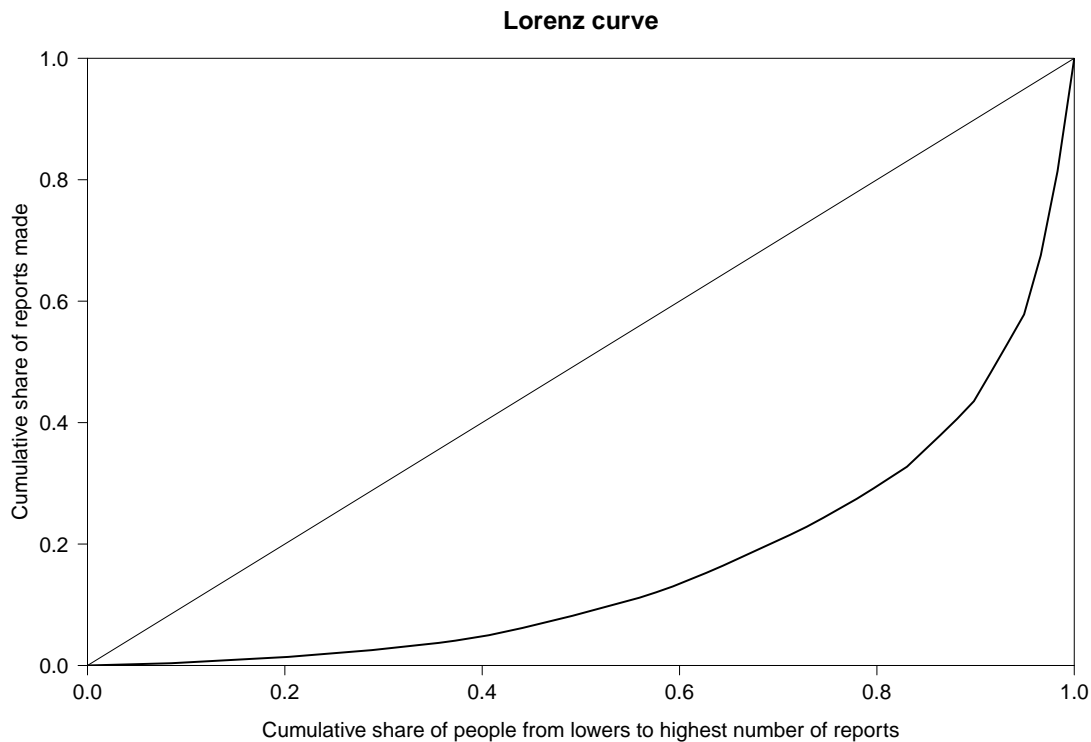
identified as 'White Other' might be over-represented.

22% (13 people) had previously experienced personal victimisation in the past 12 months. Compared with the population of the UK this sample shows the same rate of victimisation (22%) found by the CSEW in 2014 to 2015 (where 6036 out of the 27,314 people interviewed had experienced victimisation in the past 12 months).

The extent of people's participation ranged from submitting only one report throughout the entire duration of the study (5 people, or 8% of the sample), to submitting multiple times a day, consistently over the course of the 4 months. The person who submitted the most number of reports sent 250 over the 4-month study period, exactly. The average number of reports sent was 23, the median 10, standard deviation 43. Evidently, the distribution is very skewed, half of the sample submitted 10 or fewer reports. The distribution of the number of reports from each participant can be seen in the histogram in Figure 8.2, where each individual bin represents the number of reports submitted by each unique participant submitting reports about their levels of fear of crime.

This pattern of participation falls in line with the framework of crowdsourcing participants providing information, discussed already in Chapter 3, Section 3.2. But, as discussed in Section 3.2 and later in Chapter 4, section 4.3 in the case of FMS data, this is one of the great advantages of crowdsourcing, that even though there are few people who 'do most of the work', it also allows for the contribution of those many people who contribute a few times, and they are allowed to contribute "without permission, contract or instruction" (Howe, 2008). This framework is called 'micro-volunteering', in which developers structured ways of enabling minimal amounts of contributions in VGI projects (Sieber and Haklay, 2015).

This means that because this measurement tool does not limit the number of people who can contribute by setting requirements, there is not a loss of the valuable information contributed by those who contribute fewer times than others, and this perhaps serves to lessen the bias in the data towards only those who report frequently. In the case of fear of crime, the one or two reports could highlight an area that someone thought was particularly unsafe, or they could be used to cross-reference against other contributors' evaluations of an area. Observing this pattern of participation in this data supports the idea that the FOCAApp tool allows for the crowdsourcing of VGI about people's experiences with fear of crime. In fact, as I did in Chapter 4, Section 4.3 for FMS participants, I can again here produce a Lorenz curve to represent this inequality in distribution (Figure 8.3).

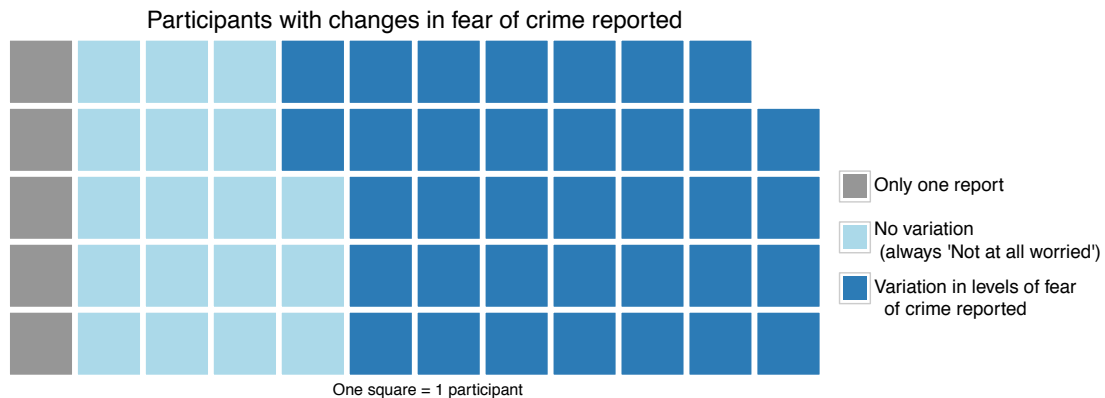
Figure 8.3: Lorenz curve for FOCAApp participants

The corresponding Gini coefficient of 0.67 is similar to that observed with FMS data (Section 4.3) and shows that both data sets follow the distribution of crowdsourced participatory data observed in prior studies. In the next section, I will use this crowdsourced data to explore the dynamic variation in fear of crime.

8.3 Descriptive analysis of within-person fluctuation in fear

The first step towards examining fear of crime as an everyday experience is to consider fluctuations in people's reported fear over time. As mentioned, of all 59 participants, 5 people submitted only one point during the entire duration of the study. For these people, it is impossible to observe a fluctuation in fear levels over time. Out of those who submitted at least two data points, 18 people sent consistently the same level of fear of crime, while the other 36 participants showed fluctuation in levels of fear over time. Further, the 18 who consistently reported one level of fear all reported being 'Not at all worried' about crime

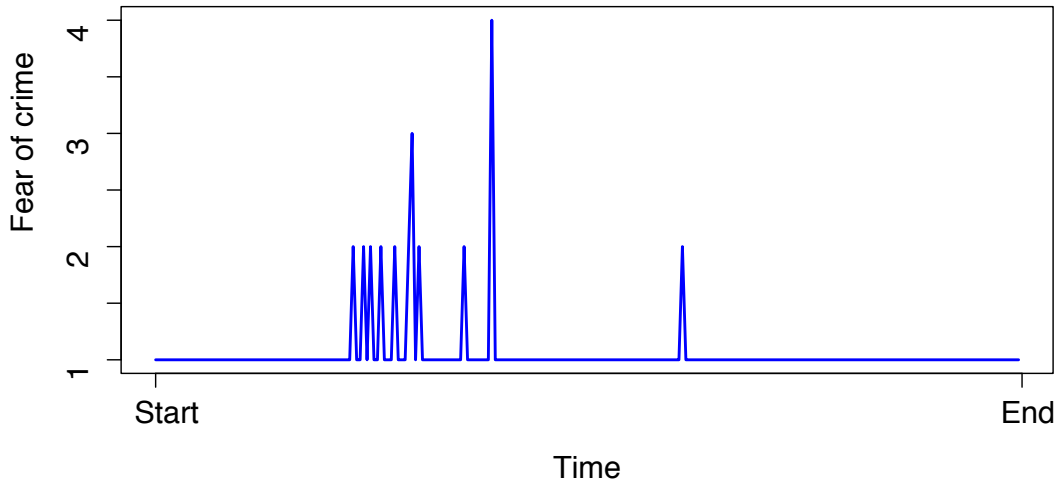
Figure 8.4: Most participants sent at least 2 reports and the majority of them showed fluctuation in fear of crime levels during the study



(Figure 8.4). Thus the only people who did not show fluctuation in worry were 'Not at all worried', so did not experience fear of crime at all during the study period.

This means that these people did not come across anything in their activity spaces for the 4-month duration of the study, which made them worried about crime, and so they remained unworried. For these people, a questionnaire asking them about the last 4-month experience would have accurately labelled them as statically unworried. However, there remained 36 participants, which is over half the sample (61%), who experienced worry, but only at certain times and places. Every participant who did experience instances of worry moved in and out of this state, and were certainly not statically or consistently worried all of the time. Notably, if this had been measured using cross-sectional surveys, some people would be recorded as statically 'Very worried', if they were surveyed at this time, as no follow up would reveal that they regress back to 'Not at all worried' over time. Whereas based on the results from the FOCApp study, it is possible to say that those people who did experience a fear of crime event were not necessarily always worried about crime. Instead, most people most of the time were 'Not at all worried' about crime, and their levels of worry increased only in certain situations at certain times, before returning to a baseline state of 'Not at all worried'. For example, Figure 8.5 shows the responses of one participant during their participation in the study. On the Y axis, each level of fear of crime is converted to a number to make the graph easier to read.

Figure 8.5: Time series of reports from one participant (fear of crime scores converted to numbers)



'Not at all worried' is 1, 'Not very worried' is 2, 'Fairly worried' is 3, and 'Very worried' is 4.

One interesting question to ask from these longitudinal patterns in people's fear of crime experience is about the interdependence of the reports. If someone experiences a fear of crime event, is their next report more likely to be a report that still contains an element of worry, before going back to a base state of 'Not at all worried'? In other words, is a fear of crime report influenced by the report that came before; does fear of crime linger?

To answer this question, it is possible to treat the data as a time series, where the frequency of the series is set to the number of reports sent (so first report submitted is t_1 , second is t_2 , third is t_3 , and so on). It is then possible to consider the interdependence of these events. A Ljung-Box test can be used to test the hypothesis that the data are not independently distributed; if the null hypothesis is rejected that means that the time series exhibit serial correlation. If significant, then the values in the series can be used to predict each other. This test helps to numerically determine whether the series itself is not a white noise process and so its movements are not completely independent from one another (Box and Pierce, 1970; Ljung and Box, 1978; Harvey and Shephard,

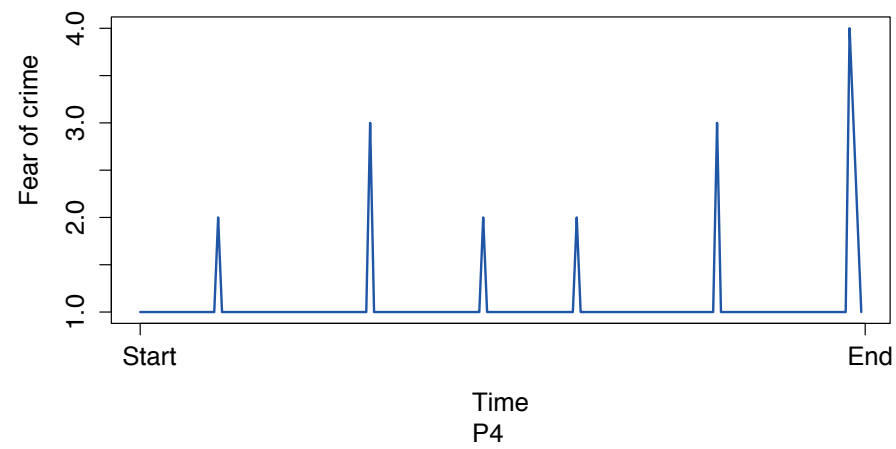
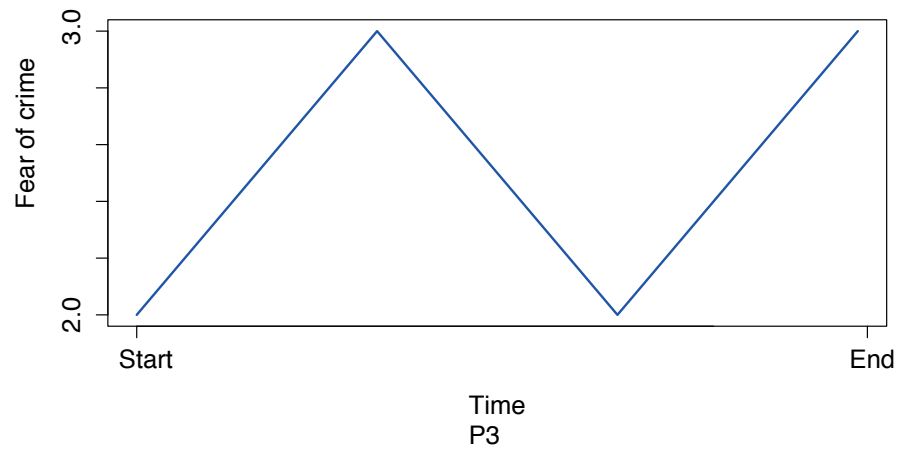
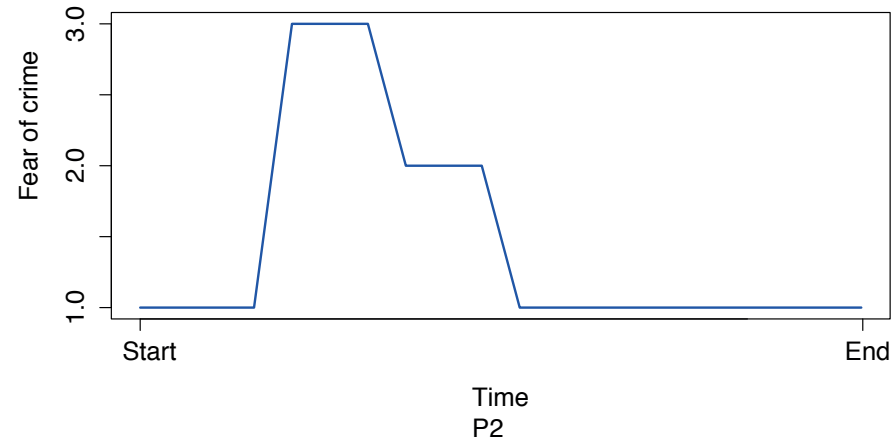
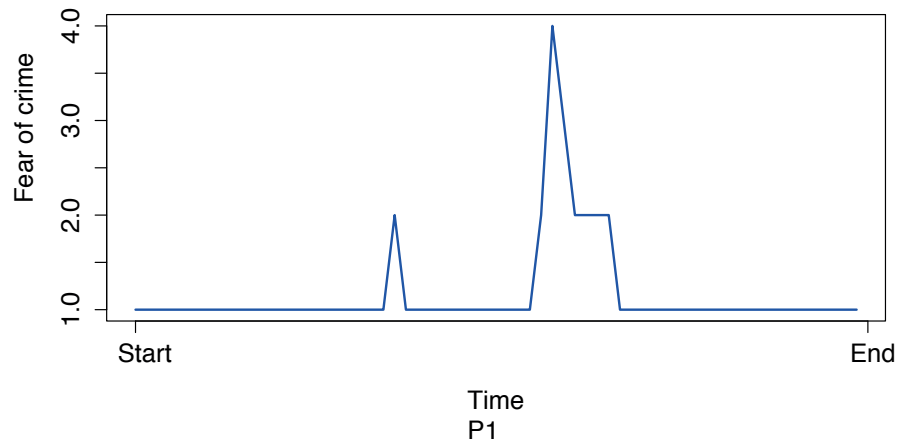
1993).

To perform this test, I iterate through each participants' responses, treating them as one series. From the 59 participants, the test is not meaningful for 23 of them; as mentioned 5 people only submitted one report, and 18 submitted consistently 'Not at all worried', so they exhibit no fluctuation in fear of crime over time. Of the remaining 36, for 32 the test results failed to reject the null hypothesis, so it cannot be concluded that their fear of crime report was influenced by the previous report. For these people, we cannot say that their fear of crime lingers. However, for 4 participants the null hypothesis was rejected, which means that these people showed a significant correlation from report to report.

In these 4 cases where the independence of the reports was rejected by the Ljung-Box test, it is possible to examine in more detail what this dependence pattern is. One participant (P3 in Figure 8.6) sent a repeating pattern of 'Not very worried' - 'Fairly worried', and one participant (P4 in Figure 8.6) showed a baseline of 'Not at all worried' that is interrupted by several spikes of worry, which show a gradual increase, then a decline, then an increase again. It is difficult to associate these patterns with an initial fear of crime experience followed by a gradual regression to 'Not at all worried'.

On the other hand, two participants (P1 and P2 in Figure 8.6) show a spike of moving from 'Not at all worried' to a higher worry state (P1 to 'Very worried' and P2 to 'Fairly worried'), which then shows a gradual decline in worry over time. These last two participants (P1 and P2 in Figure 8.6) indicate that fear of crime might linger after an initial experience.

Figure 8.6: Time series of reports from people with significant interdependence between observations (fear of crime scores converted to numbers)



These are interesting findings, as it suggests that fear of crime can be something that is triggered by an experience, but then lingers in people over time. However, based on these data, it is difficult to estimate how long. The two participants who exhibited this pattern discussed above (P1 and P2 in Figure 8.6) took different lengths of time to report 'Not at all worried' again. P1 regressed back to 'Not at all worried' in 6 days during which they submitted 6 reports (2014-11-15 14:00 to 2014-11-21 13:00), and P2 in just under a month during which they submitted 7 reports (2014-6-20 19:00 - 2014-7-15 20:00).

While with more participants this could be elaborated more robustly, even based on the above, it can be concluded that people experience fear of crime differently over time. Most people, most of the time, are not at all worried about crime. However occasionally people encounter something that makes them worried about crime, after which they return to a baseline of no worry.

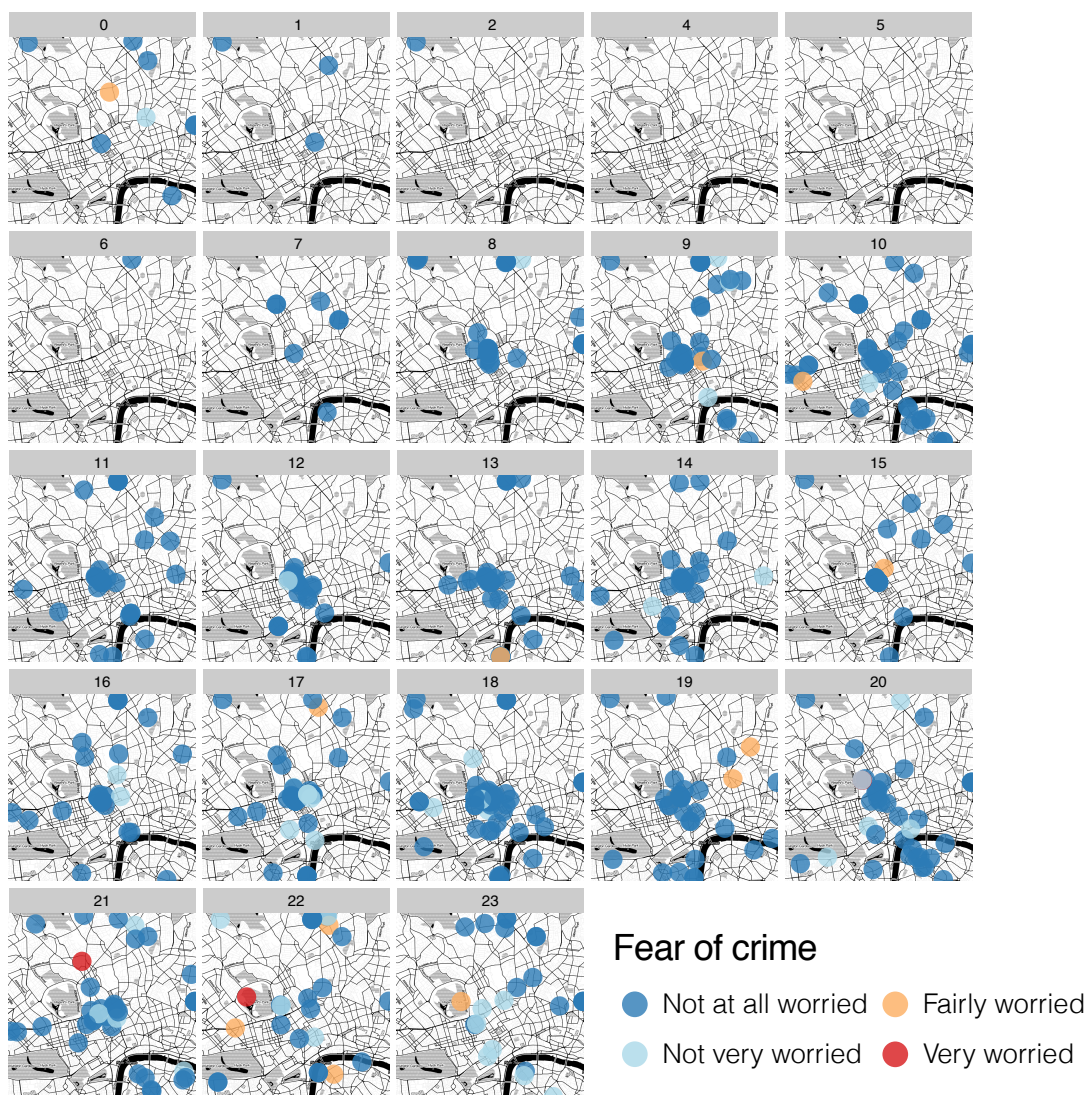
Further, fear of crime variation at such a small scale can also be explored spatially. This serves to illustrate that fear of crime can be measured on a scale that allows for the exploration of local-level interactions.

For an overview, a general map of all participants' reports can first be seen (Figure 8.7). This map illustrates the micro-level variation in fear of crime in place. The orange and red incidents of 'Fairly worried' and 'Very worried' reports are nested within reports of 'Not at all worried' and 'Very worried'. This demonstrates micro-level spatial variation in people's experiences with fear of crime.

Figure 8.7: Overview map of FOCApp reports by all participants

Further, it is possible to use this data to break down spatiotemporal variation beyond the daytime versus nighttime dichotomy. While not enough data was collected for analysis, a descriptive look into the spatiotemporal variation shows that fear of crime varies not only in place but also time. Figures 8.8 and 8.9 show variation between different days of the week, and different hours of the day.

Figure 8.8: Variation in fear of crime across days of the week

Figure 8.9: Variation in fear of crime across hours of the day

Overall, the descriptive analysis presented here hopes to illustrate that this approach to measuring fear of crime dynamically, on a micro-spatial and temporal scale, has the potential to uncover new details about people's everyday experiences with fear of crime as experienced during their routine activities, across their entire activity spaces.

This data, therefore, allows us to explore within-person variation in fear of crime and illustrates that it is a much more complex phenomenon than something that can be a static attribute of people (or neighbourhoods). When measured by cross-sectional methods, researchers gain only a snapshot of this dynamic experience, losing the longitudinal variation in fear of crime. This section demonstrated how fear of crime within an individual can vary over time, and

the next section will move on to explore the role of place, and begin to examine some covariates of fear events.

8.4 Co-variates of fear

To illustrate the importance of variation in fear with changing situations, it is possible to look at the personal and environmental variables that are associated with increased feelings of fear. As discussed in Chapter 2, Section 2.2, previous research on fear of crime has tended to focus on 'social structure' variables (Smith) as those which might influence experiences of fear of crime. These include age and gender (Lagrange and Ferraro), and previous experience with victimisation (Box et al., 1988) as key predictive factors. These questions were all asked in the demographic questionnaire part of the FOCAApp, detailed in Chapter 7, Section 7.2. Data collected using FOCAApp also measured these, so it is possible to follow the effect that these variables have on fear of crime as experienced during routine activities.

When it comes to situational factors that may affect fear, one variable repeatedly found in the previous literature to have an effect is whether the person was asked about worry in day or night time. With the time stamp attributed to each report, it is possible to also measure this using FOCAApp data. Using the same method as used in Chapter 4, Subsection 4.2.2 for reports about broken street lights to determine whether the report was made during daytime or after dark, each report was labelled as made during the day or after dark.

Additionally, another dynamic variable previously not measured is included in the FOCAApp data, and that is whether the report was made within the person's home neighbourhood or outside of it. This measure can be used as a proxy measure for familiarity with the area. As discussed in Chapter 7, Subsection 7.2.1, people were asked to provide their home postcode sector, and using the latitude and longitude collected with each fear of crime report, each report was coded according to whether it was made within this area or outside of it. This is a new, dynamic variable, that could be linked with fluctuation in levels of perceived safety within a person between situations, and can be used to test the hypothesis that people are more likely to experience fear of crime in

areas outside their own neighbourhoods, which are potentially areas they are less familiar with. If true, this would further emphasise the need to measure fear of crime in a way that addresses people's fear experiences across their entire activity spaces, including areas outside their home neighbourhoods.

This section will explore the effect of the above-listed variables on people's fear of crime as experienced during their routine activities, measured with the FOCApp approach. Subsection 8.4.1 details the analytical approach used for this data to account for its ordinal nature and nest responses from the same individual within that person, and Subsection 8.4.2 presents the results from the analyses.

8.4.1 Methods for analysis

The outcome variable of interest is an ordinal variable where people use a Likert scale to assess their feelings of worry about crime at a particular moment in time. As discussed in detail in Chapter 7, Subsection 7.1.2 the question was taken from the Crime Survey for England and Wales and was changed only to reflect that it is asking about the current moment, rather than the past 12 months. The resulting data is an ordinal variable, that ranges from 'Not at all worried' to 'Very worried'.

Ordinal response variables can be analysed with many approaches, and this section uses two of them. The first approach is to look at each individual predictor against fear of crime using chi-square tests. This serves to give an initial indication of any relationship between each predictor and fear of crime. However, the chi-square tables do not take into account the ordered nature of the fear of crime responses.

The second approach is to use a cumulative link model, to try to examine the effects of the measured variables on reported fear of crime, in a way that addresses the ordered nature of the outcome variable. This is important because "an ordinal analysis can give quite different and much more powerful results than an analysis that ignores the ordinality" (Agresti, 2010) (p.3). "Cumulative link models provide the regression framework familiar from linear models while treating the response rightfully as categorical. While cumulative link models are

not the only type of ordinal regression model, they are by far the most popular class of ordinal regression models” (Christensen, 2011) (p.3).

Additionally, as discussed in Section 8.2, different people sent different numbers of reports. Therefore, each report cannot be treated as independent, as this would bias results greatly towards representing the views of those who submit frequently, and would fail to consider the linked nature of the data. For the analysis of this data, therefore, repeated observations from the same participant must be considered as nested within each subject. Using a mixed model is one way to account for this. It is mixed because I include both fixed and random effects. The fixed effects are the ones which are known; in the case of my model here, these are gender (can be male or female), age (split into 4 groups), previous victimisation (yes or no), whether the report was made after dark (yes or no) and whether it was inside the participant’s home neighbourhood (yes or no). The random effects are the people effects. There are lots of participants, some with different propensities to experience fear of crime than others, which can be influenced by many variables which I have not included in this model. I do not want to know more about the difference between people in propensity for being worried about crime, but I do want to account for it in the model. Introducing the random effect for participants does this. A mixed model allows for such random effects as well as the fixed effects (Agresti, 2010). By using this approach, we can nest the responses within the individuals who sent them, accounting for personal biases which might affect fear of crime, characterising idiosyncratic variation due to individual differences.

8.4.2 Results

An initial glance looking at the chi-square tables shows that the cross-tabulations between fear of crime and gender, and fear of crime and previous victimisation both show no effect, with p values too large to reject the null hypothesis of no association between these variables and reported fear of crime (Table 8.1).

Further, the chi-square test for ‘age’ contains cells with less than 5 observations, violating an assumption required for the chi-square test. Unfortunately,

Table 8.1: Chi-square results for variables against fear of crime

Variable	Chi-square statistic	p value
Gender	6.67	0.35
Previous victimisation	3.09	0.38
After dark	26.59	0.00
Home neighbourhood	9.92	0.02

there are not enough data points from all age categories to allow for the slicing of the data in this detail.

However, chi-square tables for both whether the report was made in the participants' home area and whether it was made during daytime or after dark both show significant positive associations (darkness or daytime: X-squared = 26.59, df = 3, p-value = 0.00, home neighbourhood or outside: X-squared = 9.92, df = 3, p-value = 0.02).

Tables of standardised residuals show that there are more reports of 'Not at all worried' in the daytime, and more of Not very worried, 'Fairly worried', and 'Very worried' in the night time (Table 8.2). It appears that darkness might be associated with people less likely to answer that they are not at all worried. This finding is in line with findings from traditional fear of crime research (see Chapter 2, Section 2.2).

Table 8.2: Chi-square standardised residuals darkness v fear of crime

	Not at all worried	Not very worried	Fairly worried	Very worried
Daytime	4.93	-3.87	-1.89	-2.63
After dark	-4.93	3.87	1.89	2.63

People are more likely to report 'Not at all worried' in their home neighbourhood area and more likely to report 'Not very worried' or 'Fairly worried' outside of this area. (Table 8.3). The difference between reporting 'Very worried' home or elsewhere does not appear significant.

In summary, the chi-square results appear to be demonstrating that differences between groups identified by traditional approaches to measuring fear of crime (such as age or gender) do not show a significant relationship in the data collected using FOCApp. On the other hand, the more dynamic variables

Table 8.3: Chi-square standardised residuals home neighbourhood v fear of crime

	Not at all worried	Not very worried	Fairly worried	Very worried
Home area	-2.99	1.98	2.05	1.20
Outside	2.99	-1.98	-2.05	-1.20

that describe fluctuation in situations, such as whether the person was in their home neighbourhood or not, and whether it was daytime or after dark, do show a relationship with fear of crime.

However, as mentioned in Subsection 8.4.1, relying on chi-square test alone would not take into account the ordered nature of this data, and so a cumulative link model is used. This serves to assess the effect of the explanatory variables included in the model on fear of crime, while also accounting for unmeasured between-person variation in reporting by taking the participant effects to be random.

The results from this analysis are very interesting - none of the factors traditionally associated with increased fear (age or gender or previous victimisation) showed a significant effect in the FOCApp data (Table 8.4) .

Table 8.4: Results from cumulative link model for fear of crime

	Location coefficients			
	Estimate	Standard Error	z value	p-value
Gender (Male)	-0.82	0.53	-1.56	0.12
Age Group 30-40	-0.99	0.61	-1.62	0.10
Age Group 40-50	-0.6	1.52	-0.39	0.69
Age Group 50 or over	-15.5	265.27	-0.06	0.95
Previous Victimization (Yes)	-0.14	0.71	-0.20	0.84
Dark (Yes)	0.93	0.23	4.01	0.00
Home neighbourhood (Yes)	-0.78	0.30	-2.59	0.01

The only variables that seem to have a statistically significant effect are whether or not the report came from within a participant's home or work post-code area, or whether the report was made after dark, or during daylight hours (see Chapter 7, Section 7.2 for details on how these variables were measured). The condition number of a model measures how much of the output value can change for a small change in the input argument, and can be used to measure how sensitive a model is to change or errors in the input. The condition number

of the Hessian for this model is 4173964.43. High numbers, for example, larger than 10^4 or 10^6 indicate that the model is ill-defined (Christensen, 2015). This would indicate that the model can be simplified, that possibly some parameters are not identifiable, and that optimisation of the model can be difficult (Christensen, 2015). In this case, the condition number of the Hessian measure of fit does indicate a problem with the model.

As discussed above with the chi-square analysis, however, there are not enough data to consider the age of participants. Once the age variable is removed from the model, the condition number of the Hessian drops to 223.54. While this indicates that the model might no longer have problems, the remaining personal variables, gender and previous victimisation still have p values greater than 0.05, and are not statistically significant predictors in the model (Table 8.5).

Table 8.5: Results from cumulative link model for fear of crime without age

	Location coefficients			
	Estimate	Standard Error	z value	p-value
Gender (Male)	-0.23	0.76	-0.30	0.77
Previous Victimization (Yes)	-0.96	1.49	-0.64	0.52
Dark (Yes)	1.17	0.35	3.35	0.00
Home neighbourhood (Yes)	-0.83	0.35	-2.41	0.02

If I were to remove all the personal variables and keep only the situational variables, then the condition number of Hessian drops to 29.74, which would not indicate a problem with the model.

The best model, as indicated by the Hessian score, is the one with only the situational variables in it, and this new model is show in Table 8.6.

Table 8.6: Model with only situational predictor variables

	Location coefficients			
	Estimate	Standard Error	z value	p-value
Dark (Yes)	0.97	0.23	4.31	0.00
Home neighbourhood (Yes)	-0.91	0.3	-3.04	0.01

The coefficient for darkness is positive, indicating that when it is dark, higher fear of crime reports increase, which means that reporting in higher

categories of fear is more likely in darkness. This is in line with previous research, as well as the chi-square results above. The coefficient for being in one's home neighbourhood, on the other hand, is negative, which means that when people are within their own neighbourhood, reporting in higher categories is less likely than when they are outside of this area. Again this matches the chi-square results and is in line with the original hypothesis that people are more likely to experience something that makes them worried outside of their home neighbourhoods, proposed at the start of Section 8.4. This finding reinforces the need for a measurement of fear of crime which addresses people's entire activity spaces, not just their home or work neighbourhoods.

These findings seem to indicate that situational factors are significant predictors of experiencing fear of crime as part of one's routine activities. However, none of the personal variables showed up as significant. Does this mean that individual variation in the propensity to experience fear of crime does not matter? In fact, no. As mentioned earlier in Subsection 8.4.1, I included a random effect, for the 'subject effect' (this means the effect of the participants).

For random effects in a model, a likelihood ratio test can be used as a means to attain p-values. The likelihood is the probability of seeing the data collected given the model (Winter, 2013). The logic of the likelihood ratio test is to compare the likelihood of two models with each other; the model without the random effect (this is the null model), with the model with the random effect¹.

Table 8.7: Result of likelihood ratio test

	AIC	p value
Null model (no subject effect)	500.57	
Model with subject effect	465.89	0.001

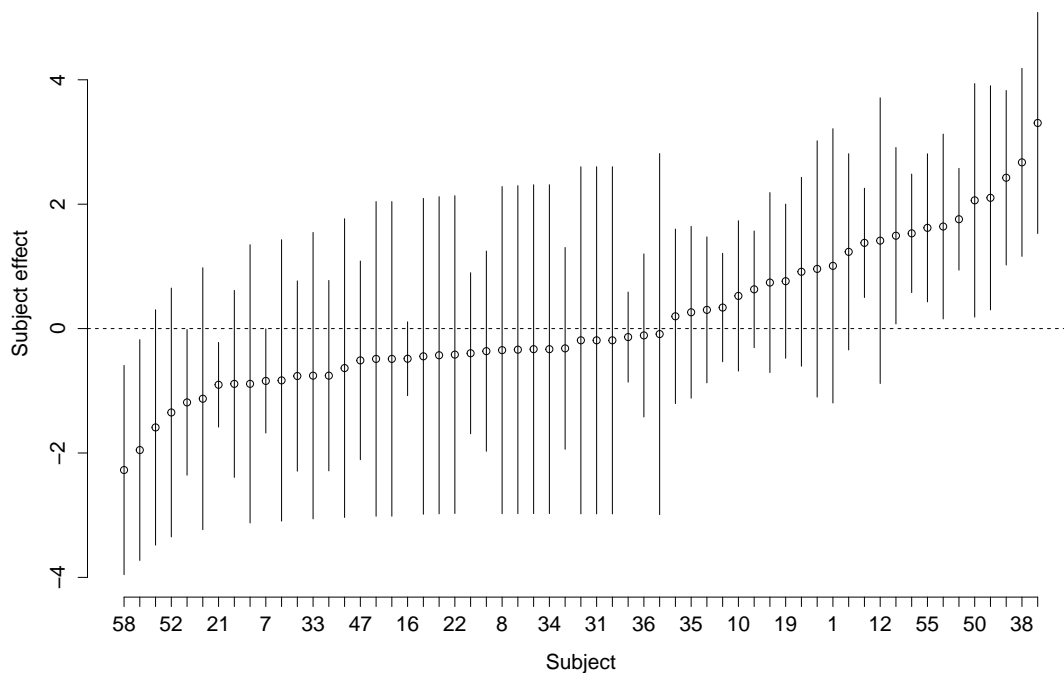
Table 8.7 shows the results from the likelihood ratio test to compare the model with the random effect to a model without it. It returns a p-value of 0.001, indicating that the subject term is significant. Also, as in Chapters 5 and 6, Sections 5.2 and 6.1, the Akaike information criterion (AIC) can be used here as well to assess whether the model with the subject effect is a better fit than

¹I performed the likelihood ratio test using the `anova()` function in R

the null model without. The model with the smaller AIC value is the preferred model, which in this case is the model with the subject effects included (Table 8.7). Overall it can be concluded that subject effects are important. These quantities are plotted in Figure 8.10 illustrating subject effects via conditional modes with 95% confidence intervals based on the conditional variance.

These subject effects are not parameters, so they cannot be estimated in the conventional sense, but a 'best guess' value can be retrieved from the model for each participant. This is called a prediction, or more generally a conditional mode. The conditional variance can then be used to provide an uncertainty measure of these conditional modes (Christensen, 2015).

Figure 8.10: Subject effects via conditional modes with 95% confidence intervals based on the conditional variance



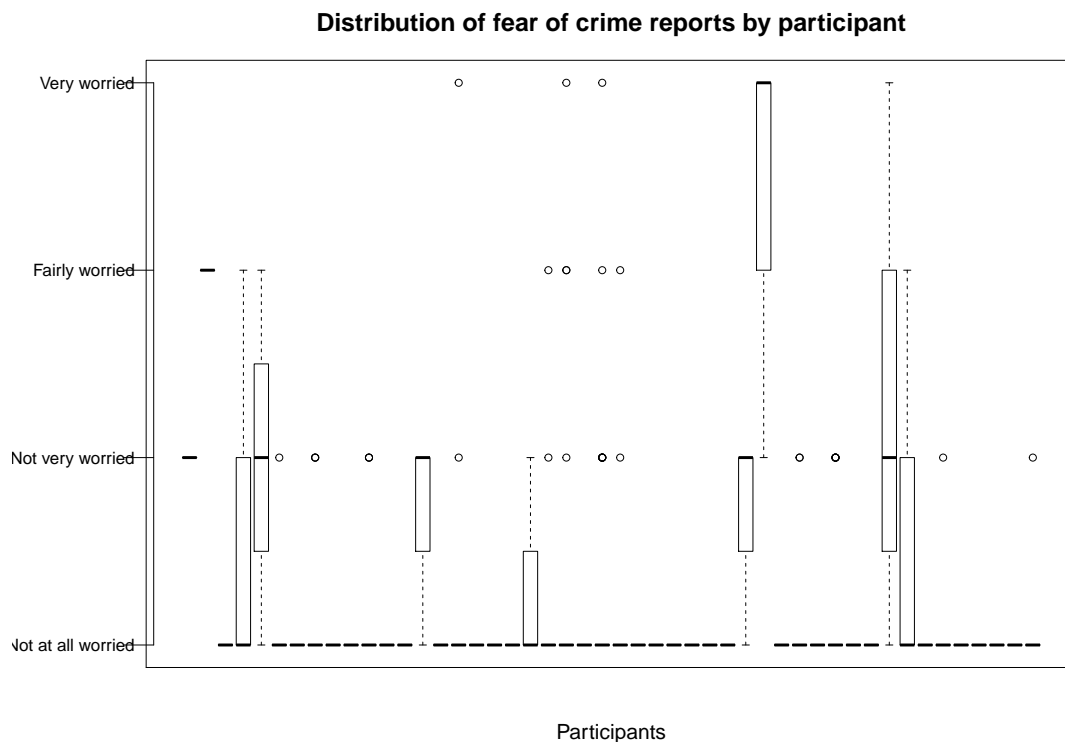
So Figure 8.10 shows subject effects for each participant. Each participant is labelled with a number (1 through 59) and arranged by subject effect order (so participant '58' gave the lowest fear of crime scores responses, while participant '39' gave the highest, with response coded 1 to 4, 1 for 'Not at all worried', and 4 for 'Very worried'). The dot represents how the subject effect for each participant deviates from zero, and the lines provide a 95% confidence

interval. This figure serves to illustrate that there are individual level factors that people bring with themselves which influence their fear of crime, as well as the situational factors.

The results of significant subject effects imply that people (subjects) experience fear of crime differently. Two natural interpretations are that either a level of fear of crime of, for example, 'Not very worried' means different things to different people, or the subjects actually experienced fear of crime differently as they move across different activity spaces. Possibly both effects play their part. This serves to illustrate that while situational factors were the only variables captured by the FOCApp data collection method that showed up as significantly influencing people's likelihood of experiencing fear of crime events, individual factors also play a significant part. This is further reinforced by looking at the distribution of fear of crime reports within participants. Figure 8.11 shows a boxplot² for each participant showing the distribution of all of their fear of crime reports while participating in the study. This illustrates that while most participants report being 'Not at all worried' most of the time, with other levels of worry as outliers, there are participants who report higher levels of worry. The distribution of responses varies between people. However, what these factors are, that influences people's propensity to feel worried about crime, were not captured in the data here.

While these results present some interesting insight into how fear of crime varies across changes in situational context, the spatial and temporal granularity of the data has not been exploited to its full capacity. Fear of crime is something that people do not often experience; it is a relatively rare event when measured this way, and therefore in this study, not enough data was collected to slice the data up in more detail. However, there is potential for this with the FOCApp data collection technique, and Section 8.3 provided some descriptive analysis into micro-level variation in fear of crime across time and place, which could be built upon with more such data. And there is also demand for

²The bottom and top of the box are the first and third quartiles, the band inside the box is the second quartile (the median), the ends of the whiskers are the lowest datum still within 1.5 IQR of the lower quartile, and the highest datum still within 1.5 IQR of the upper quartile, and the circles represent outliers

Figure 8.11: Distribution of fear of crime reports within participants

collection and analysis of fear of crime measured from this approach.

The next section will serve to illustrate that not only is it possible to collect such data, but that there are practical implications for being able to do so. There are organisations who would benefit from the application of this methodology to their specific areas of interest, to be able to collect information to inform targeted approaches to reducing the fear of crime.

8.5 Applications and impact

While the results presented in Section 8.4 are limited due to the relatively small number of participants, they serve as a proof of concept for a tool that did not exist previously, for measuring people's experiences with fear of crime in a way that ties to specific situational contexts. The need for such measurement is illustrated by the interest expressed in FOCApp by two different groups, which will be discussed in this section.

8.5.1 Mapping fear of hate crime in Camden

The first organisation to show interest in using FOCAApp was the Camden LGBT forum, a nonprofit charity working to offer support to people who live, work, or 'play' in the London borough of Camden. Their main concern is around the under-reporting of hate crime, which results in a low volume of data around hate crime. This low number means that they do not have adequate data to identify problem areas, or to lobby for change. They thought that by using FOCAApp can better identify the best times and places for them to target interventions, or to build evidence in order to lobby the local authority or other bodies for change to reduce the prevalence of hate crime.

One barrier to learning more about hate crime is that most anti-gay hate crimes are never reported (Herek, 1989). There is significant research to show that many hate crimes are not reported to the police for fear of discrimination from the police or at other stages of the criminal justice system such as by a judge (Dick, 2009). Victims might also fear being 'outed' if the case went to court (Cogan, 2002). However, more recent work has found that the most common reason victims do not report hate crime incidents is that they do not think that the incident is serious enough, and conclude either that the police could not do anything about it, that the police would not take the incident seriously, or often it is the victim themselves who do not think that the incident was an offence (Dick, 2009).

In turn, a Case and Outreach Worker from Camden LGBT Forum hypothesised that if the task for people experiencing hate crime was to report fear of hate crime, rather than an incident that requires proof, these issues might be mitigated. By reporting through an application, anonymity would be ensured, so people would not get 'outed' by making a report, and further they would not face any members of the criminal justice system, so would not have to worry about being treated unfairly. Also, reporting *perception* of crime rather than incidents themselves, removes the need for having to interpret something as an offence, it is enough to note that the person felt unsafe; as long as the person felt unsafe in that situation, they are encouraged to report it. It was hoped that

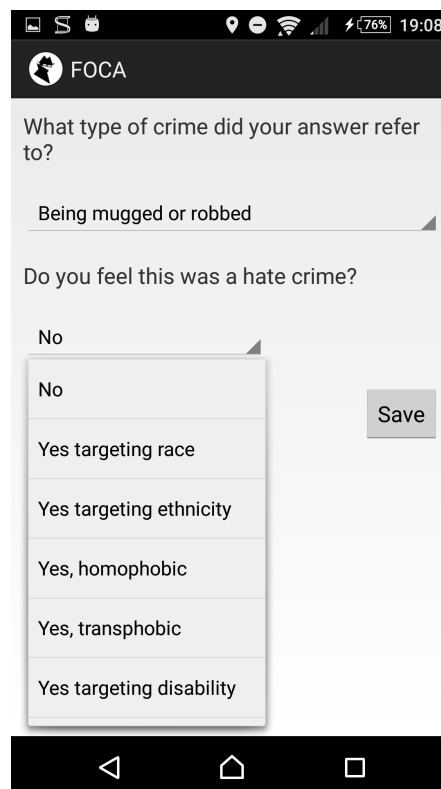
this way, the FOCAApp would facilitate the reporting of worry about hate crime specifically, and help highlight areas of concern for the Camden LGBT forum to then tackle with interventions.

In order to assess whether this would be a feasible option for people to use for the reporting of hate crime, I attended a meetup of the Trans London group, where I was allowed to demonstrate the application, and explain its potential benefits to members of the group. The session lasted one hour, of which the first 15 minutes were the demonstration, followed by 45 minutes of discussion. There were altogether 17 people in attendance. From the discussion, it became evident that this group had all experienced personal victimisation regularly, and that they were happy to share their experiences, but did not think that there would be anything that could be done about it. Multiple people who spoke up discussed their experiences with harassment that is part of their everyday lives, and no matter where their routine activities took them, they experienced fear of crime and personal victimisation. Many people cited victimisation in their own homes, by neighbours, and had detailed how they actually had the police involved, but who were unable to provide any long-term solutions to their issues.

Due to these issues mentioned above, most people in the group were unconvinced that the data collection tool will yield any benefit for their daily lives. Despite this, people agreed to take part in a trial of the application. As a result of this meeting, I had changed the application to allow for the selection of non-binary gender options, and also to ask on the last page of the application, whether the topic of the report was a hate crime (Figure 8.12). The tool has not been deployed on a wider scale. This experience demonstrates the potential application of this tool to real-world problems, to assist practitioners in collecting data which they do not currently hold or have means to collect.

8.5.2 Mapping fear of crime on an East London bus route

The second organisation to approach me was a project group from the local transport authority, Transport for London (TfL), who were working on increasing perception of safety on an East London bus route. They were interested in

Figure 8.12: Changes to FOCAApp

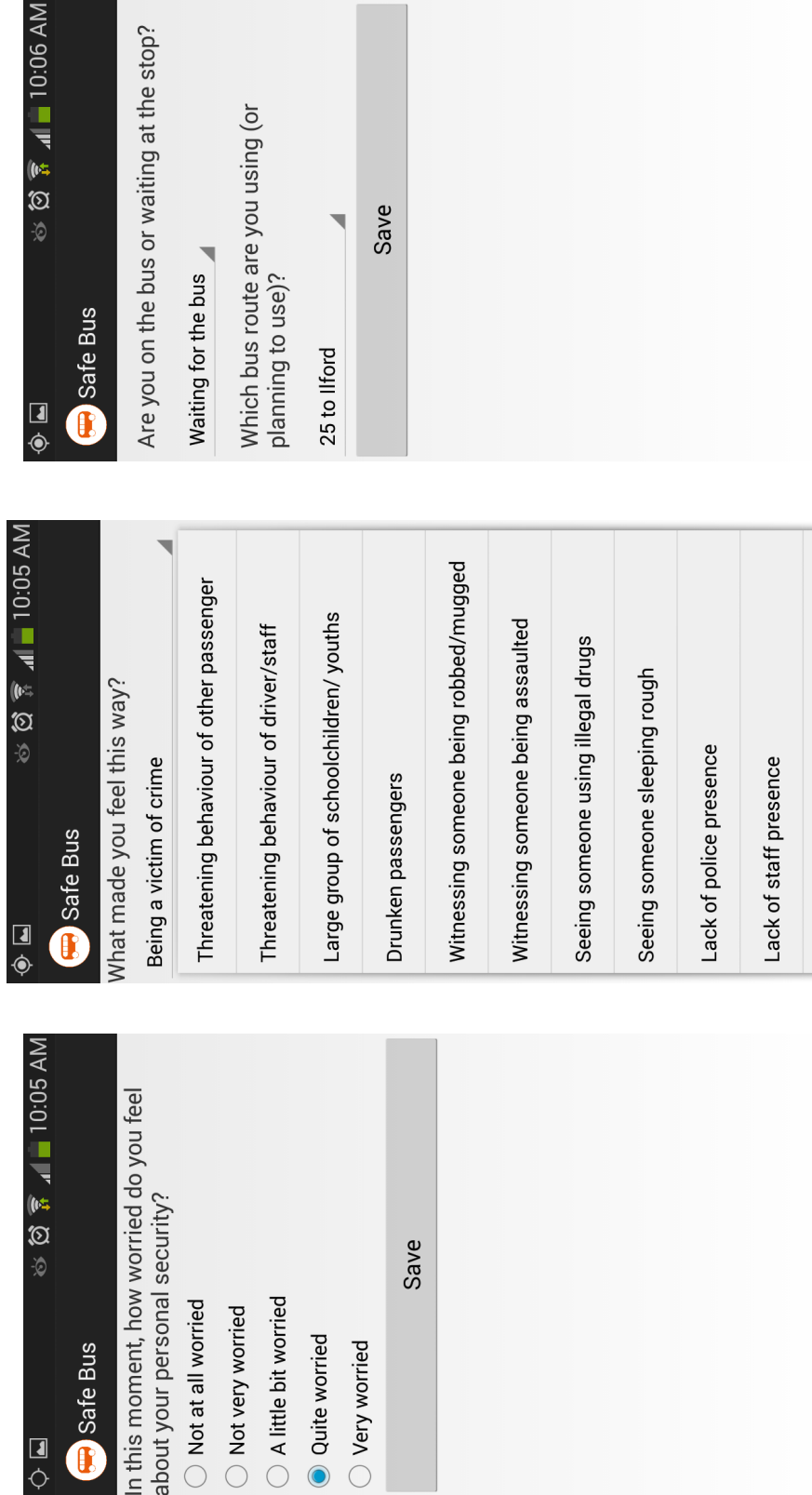
measuring fear of crime along a specific bus route, to be able to identify where exactly along the route people felt unsafe, and to target those areas with more high visibility policing, and also more presence of revenue protection inspectors (RPIs), with the hope to increase confidence and reduce fear. Officer and RPI time is limited, and this bus route is one of the longest in London, and runs 24 hours. Because of this, any intervention needs to be targeted, so identifying specific locations and times along the route where people felt unsafe is necessary for tasking.

In order to measure fear of crime along a bus route and to meet TfL's specifications, the application needed to be substantially altered. Questions were changed from the CSEW questions to match question from TfL's own Attitudes to Safety and Security survey, their bespoke measure of confidence and fear of crime on the transport network. Additionally, a map layer of the bus route needed to be added to the map for the retrospective annotation option, so that it would be easier to report the incident retrospectively. Also, temporal pings were no longer fit for purpose, as instead of at specific times of day,

the interest became geographical, and TfL were interested in how people felt when they were using that particular bus route regardless of the time. It was unreasonable to ping people at all hours of the day because they may not be anywhere near the route, which was the area of interest. Instead, pings were programmed to be location proximity based. Whenever the user was within 400 meters of any of the bus stops for the route 25 (400m is the recommended distance between bus stops according to TfL guidance (Transport for London, 2006)) they were sent a notification to complete the fear of crime questions from the Attitudes survey. The new question asked 'In this moment, how worried do you feel about your personal security?', to which people could choose from: 'Not at all worried', 'Not very worried', 'A little bit worried', 'Quite worried', or 'Very worried' as answers (Figure 8.13a). Additionally, as mentioned in Chapter 7, Section 7.2, if the participant answered with a higher level of worry, they were presented with a list of options to select what made them feel this way. This was also changed to match the options from the Attitudes survey (Figure 8.13b). Finally, two additional questions were introduced, to ask participants whether they were on board the bus or waiting for the bus at the time of answering (or at the time of incident, in case it was a retrospective report), and their direction of travel (as the single GPS reading is not able to provide this information) (Figure 8.13c).

The application was trialled with RPIs, for one shift. The trial involved 15 RPIs, who were interviewed together in a de-briefing focus group after the shift. They were asked about using the application, and also to describe their experiences with fear of crime. Figure 8.14 shows the results from all reports, while Figure 8.15 shows results broken down by whether the RPI was on board the bus or waiting for it, assessed by a question asked by the application. This distinction was deemed important for TfL to be able to assess whether any intervention in an emerging hotspot would have to focus on the bus or the bus stop.

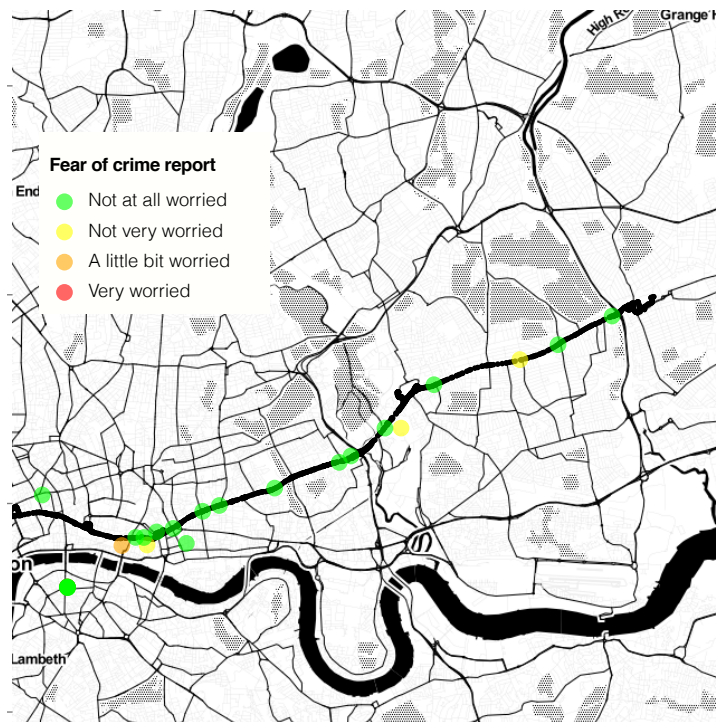
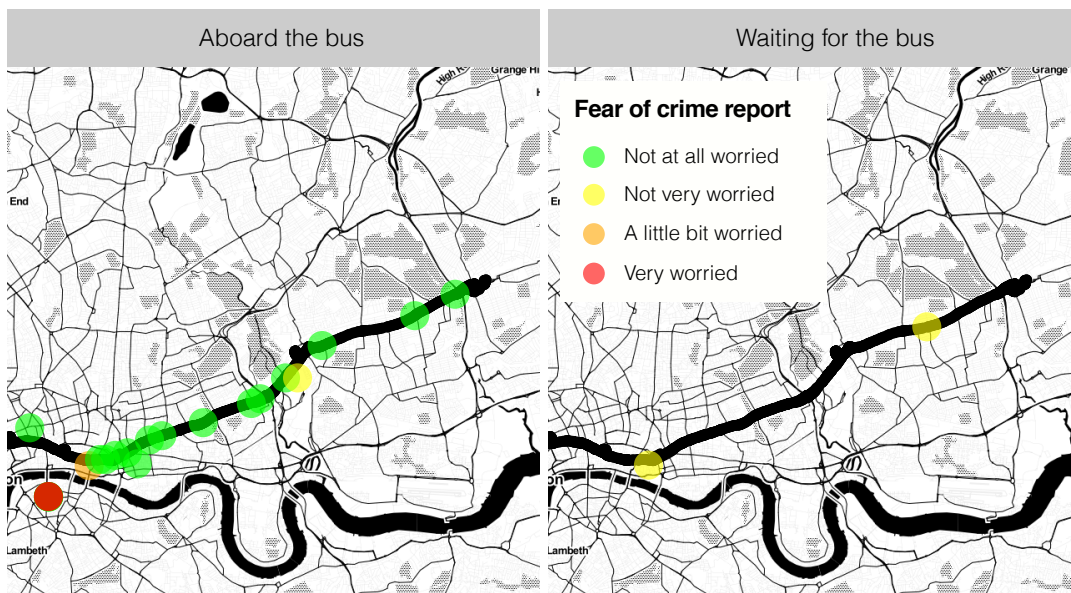
Results from the focus group indicate that in terms of using the application, the app itself is very easy to use, but as part of their job there are too many other things RPIs must concentrate on. However, for passengers, it was



reka.solymski.uci@gmail.com

(a) Fear of crime question in Bus App **(b)** Selection of possible reasons for feeling worried from Attitudes survey **(c)** Additional questions for Bus app

Figure 8.13: Changes to application for use by TfL as Bus app

Figure 8.14: RPI trial of measuring fear of crime along bus route**Figure 8.15:** Fear of crime along bus route on board the bus vs at stop

suggested that they might be less distracted, and have more time to fill out the app. Regarding the length of the app, most RPIs appreciated that it was quick to complete. One person commented:

"I've filled it out. Not many times, but each time it worked and was quick to

do”

However, one person mentioned that it was actually too short and that they felt that additional fields would improve the quality of data collected:

“It’s too short. It needs extra free text entry where I can express why I’m worried or why I’m feeling safe. Something like an optional comments box.”

When speaking about their fear of crime, RPIs appeared to represent a group where the majority of them experience direct victimisation more frequently than the general population. One RPI said:

“We deal with it day in day out, it is normal everyday experience. In this way we are different, we have a different experience from passengers.”

However, they still emphasised fluctuation in their experience, either with different conditions, such as levels of crowding on the bus:

“It does vary, some times are worse than others for example when it’s very crowded it’s worse”

Or with time of day:

“It’s different at different times of day, it’s worse at peak times, early mornings, late night, closing time of bars and clubs, when they all get on the bus to go home, about 4 to 6am is the worst. And Sunday morning, the early morning drunks. Also rush hour, after school when the school kids get on the bus.”

These comments indicate that this group experiences different levels of fear of crime and even victimisation, by nature of their varying routine activities as part of their job. Future work could identify personal characteristics that indicate different routine activities, and therefore different experiences with fear of crime, beyond demographic distinctions, considering instead differences in activity patterns.

Overall, this pilot showed the transferability of FOCAApp and its potential for measuring fear of crime along a bus route. Due to some internal issues, and the person leading the project leaving the team, the study with passengers did not take off, however, it still shows that there are many potential applications for this data collection tool, that remain to be explored in the future.

These case studies included here demonstrate that this proof of concept for measuring fear of crime as an event experienced in everyday life, with spatial

and temporal components has not only value in advancing what is known about fear of crime in crime research, but has also practical uses, which could be further pursued to benefit various organisations, and show real world impact as well.

8.6 Discussion

Overall, while these results are based on a small sample, they serve as a detailed illustration and proof of concept for this approach of utilising new methods and digital platforms to generate novel data, which functions as a provocation to the field. In promoting the exploration and collection of such new data on people's everyday experiences with crime and place, this approach can provide a template for generating new perspectives on fear of crime.

Sections 8.3 and 8.4 of this chapter present the findings from the study which followed participants during their routine activities using the FOCAApp measurement tool to find out about their everyday experiences with fear of crime. Results from this study demonstrate that people's experiences with fear of crime fluctuate over time and with changes in situational context. Therefore this data collection method provides a way to measure the situational covariates of fear of crime.

One interesting finding comes from the result that none of the social structure variables, which are conventionally found to influence fear of crime showed up as significant in this data. In the case of age, as discussed earlier, this might be due to having not enough participants for meaningful analysis. For example, there were only three participants aged between 40 and 50, and only two 50 or over. However, for other categories, this indicates that as people move in and out of different environments at different times, their experience of fear of crime changes.

This does not mean, however, that individual effects do not matter. The model in Section 8.4.2 further revealed that there were differences between people in the levels of fear of crime they reported; who the report came from also affected what the report was. Of course, these people did not follow the same routine activities, and it is possible that it is some systematic difference

in their routine activities causes these differences, rather than innate or demographic characteristics. In any case, the personal propensity for experiencing fear of crime should not be discounted, and should be explored alongside the situational factors.

However, from the results presented here, it emerges that factors that vary across situations, such as levels of darkness, or being within an area that the person is familiar with, show a statistically significant effect on reported fear of crime. This suggests that situational variables associated with experiencing fear of crime events can explain some variations in fear which are not explained by static, demographic variables. This finding strongly reinforces the hypothesis that fear of crime is context-dependent.

Besides illustrating a contextual variation in fear, the finding that that people might be more likely to be worried in an area where they are unfamiliar, and perhaps not as much in their home neighbourhoods, has implications for traditional approaches to studying fear of crime. Traditional questionnaire surveys tend to ask people about levels of fear of crime within their own neighbourhoods. The results presented here suggest that people are actually more likely to encounter instances of fear of crime outside their own neighbourhoods. This finding serves to highlight the importance of longitudinal measurement of fear of crime that targets people's entire activity space, alongside the use of cross-sectional surveys. Evidently, (at this time) novel technology of web-enabled smartphones and their built-in sensors could be used, in order to collect new data, and uncover new dimensions to fear of crime as a dynamic function of people's routine activities.

In itself, however, it is important to understand that it is not often that people feel afraid. Unfortunately, this renders the data on fear events too sparse to attempt any sort of meaningful hotspot analysis, let alone spatiotemporal analysis. While FOCAApp results also found a temporal effect in the traditional day versus after dark dichotomy, with more data, it would be possible to break time down even further, and into different temporal categories. It could be possible to look to differences between weekdays and weekend, and even between hours of the day, to find seasonal patterns in fear of crime. Section 8.3 illustrated the

potential for this with some descriptive examples, and, these results provide a glimpse into the wealth of new insight into people's everyday experiences of fear of crime at such a micro-resolution of place, that is made possible through the data gathered using this methodology.

One issue with measuring fear of crime in this way, however, is one that persists with measuring anything subjective; what is returned is a function of what is asked and how it was asked. Essentially, Jackson and Gouseti (2015) point out that "the methodology may affect the very thing that it measures by sensitising people to crime and risk" (p.213) . The more people think about crime, they might experience more fear of crime. By making crime more psychologically proximate, the application makes crime more salient in participants' minds, and so they may become more sensitive to 'signs of crime' in the environment (such as signal disorders discussed in Chapter 2, Section 2.3). There is even a potential ethical dilemma that might come as a consequence of actually creating fear of crime within people, by asking them about their fear so constantly.

If constant exposure to the question about fear of crime leads to increased salience and in turn increased worry, there should be a gradual increase in fear levels or at least the frequency of fear levels. However, in this study, the temporal analysis of people's fear of crime over time did not reveal such a relationship. While within the sample an increase in fear of crime over time was not demonstrable as the study progressed, which is what should happen if this were the case, it is possible that on a wider scale this would occur in some participants, and this is something that should ideally be avoided.

One possibility to overcome this issue would be to extend the survey period, and allow for days to pass without pings potentially allowing respondents to not constantly and daily think of the survey, which may lead to more realistic responses (Leitner and Kounadi, 2015). However, beyond that, it is difficult to move away from finding out about people's experiences with fear of crime without asking them about it. One approach in the future could be to make use of sensors, and take physiological reactions as proxy measures for fear events. Such measures bring with them their own set of complications, but could po-

tentially offer a way to eliminate outwardly asking participants about their fear, which might influence the phenomena of interest itself.

Another limitation, which remains generally true for all the crowdsourced data in this thesis as outside, is that of unequal coverage of different areas. An aerial mapping unit (e.g., block, street, or location) for which a large number of fear of crime responses were collected will depict fear of crime levels more accurately than for a unit that has only one response. The amount of responses per unit or a minimum number of responses (if fear of crime is to be averaged over the unit) should, therefore, be considered, which would require a fairly large sample size (Leitner and Kounadi, 2015). Related is the problem of people avoiding the areas where they are truly worried. While "some people cannot engage in such avoidance behaviours, some do, and this poses challenges in terms of how one might capture valid and reliable data on the most fear-inducing environments" (Innes, 2015) (p.217). One possible mitigation would be to combine with the approach of Doran and Burgess (2012) using cognitive mapping to ask people what areas they avoid due to it being associated with high fear of crime. The multiple maps could be combined to create a complete picture of both where people experience fear of crime during their routine activities, and where people avoid based on their generalised fear and diffuse perception of places.

The main contribution of the FOCAApp approach as covered in Chapters 7 and 8 is that it has the potential to illustrate spatial and temporal variance in fear of crime, as highlighted in Section 8.3. This frames fear of crime as an everyday experience, focusing on how particular issues and situations occasion certain responses and reactions (Innes, 2015). This approach offers the potential to provide a new take on social reactions to crime, antisocial behaviour, and control interventions, that, with more participation and responses can be used to identify areas of under-reported crimes, such as hate crimes against LGBT people (Subsection 8.5.1). It also has potential to gauge the effectiveness of interventions designed to manage and reduce levels of fear, particularly at small area level (Innes, 2015). The usefulness of measuring fear of crime on a specific spatial resolution to assess the effects of an intervention are also

illustrated by the interest from Transport for London to incorporate the app into their project to measure fear of crime on a specific bus route, along which they were carrying out various engagement and fear-reducing interventions (Sub-section 8.5.2).

Another important contribution of this approach is that the crowdsourced nature of the FOCAApp "allows the delineation of more accurate spatial and temporal clusters of fear of crime" (Leitner and Kounadi, 2015). While using spatially aggregated representations of the data for visualisation and analysis is very valuable, this new dimension introduces a level of granularity that was not previously available for perception of crime and place research, and can help address or even begin to just measure the extent of the unavoidable issues with averaging and aggregating of individual information. For example, a common issue with aggregating point-level data to various area-level units is the modifiable areal unit problem, which highlights how different choice of boundaries can lead to different outcomes (Openshaw, 1984). This is an important issue that needs to be taken into consideration when mapping fear of crime and the spatial granularity of the measurement approach presented here can provide a means for exploring this further (Leitner and Kounadi, 2015).

Overall, if this study was to be conducted with an assurance for people to participate by providing some sort of feedback, the same way that Fix My Street can promise that if an issue gets reported they will send it on to the local authority who will then address the problem (see Chapter 4, Section 4.1), then it has the potential to provide a cheap way to gather large amount of data, at a granularity that allows for new types of analysis into people's fear of crime and its dynamic variation in place and time, with changes in the situational context.

Chapter 9

Discussion

By recording spatial and temporal information about when and where people experience fear of crime, encounter disorders, or act as active guardians monitoring their environments, new insight can be gained into the dynamic nature of these phenomena. The main contribution of this thesis is to illustrate how this can be achieved through making use of already available crowdsourced data, or through using new technology to create bespoke data collection tools to gather the relevant information. While some of these approaches are being explored to look at getting information about crime risk for example, this thesis is the first instance of applying such data to the study of people's subjective perceptions of disorder and safety in their environments, to make inferences about the connections between their routine activities, and their subjective perceptions and dynamic experiences, at such micro-level spatial and temporal granularity.

While the place-based study of crime has been widely accepted in criminology research, framing *perception* of crime and place as a situation-dependent experience that people encounter during their routine activities is a novel approach, presented in detail in this thesis. By making use of crowdsourced data, I have contributed new insight to the vast literature around the study of the perception of crime and place. This was made possible by utilising developments in data collection methodologies afforded by the increased prevalence of mobile technologies. While questionnaire surveys have dominated research into people's perceptions of their environments, and have provided a well-tested and reliable means to gather information about how people react to crime (and

even about people's routine activities, in the case of time use surveys) this thesis hopes to demonstrate that new techniques can add further detail for exploration of new features of these concepts.

Chapters 5, Section 5.4, Chapter 6 Section 6.3 and 6.4, 7 Section 7.3.2, and Chapter 8, Sections 8.3 and 8.4 all demonstrate that crowdsourced data can result in spatially and temporally explicit information about phenomena that have previously been very difficult to map in such detail. If uptake is high enough, such data can provide novel insight into how people experience fear of crime, and what factors influence its variation. The potential applications of such a tool were illustrated by two case studies in Chapter 8 where organisations requested this tool and the possible data from it. This indicates that such data are useful in order to be able to improve organisations' everyday workings and services. The potential for this is great, given the right approach and time scale, such tool can provide a solution for mapping subjective perception of place.

Of course, as with any new technique, many challenges also emerged, and those will be discussed in Section 9.1. These limitations are important to address in order to be able to tackle them in future work, and to make sure they are kept in mind when interpreting results. Then Section 9.2 will summarise the findings from this thesis, and Section 9.3 will discuss the new insights gained through the approach used throughout. Section 9.4 will list some suggestions for future research to build on the contributions of this thesis, and Section 9.5 will emphasise the potential implications for policy and practice. Finally Section 9.6 will offer concluding remarks and bring this thesis to a close.

9.1 Limitations

Due to the novelty of the approaches taken here, there are many limitations, discussed in detail with each approach in their respective chapters. The use of this type of data raises some research challenges. Empirical examples presented in Chapter 4 Section 4.3, and Chapter 8, Section 8.3 demonstrated some of these; the potential 'over-influence' of super-contributors in VGI datasets and the restriction of results using primary collection tools such as mobile phone

apps to those likely to get involved in such activities. More generally, a very important limitation of both crowdsourced data and data collected with new technologies is the bias inherent in the sampling. In the case of using new technology, the sample systematically excludes those who do not have access to this new technology, which can result in a lack of data about certain age groups or other demographics in the sampling. In the case of relying on crowdsourced data, the sample is entirely self-selected and out of the researcher's hands, giving way for people more motivated to speak about the issue to voice their concerns, and leaving out those who do not participate so extensively, but might still be affected. This is something to keep in mind when drawing conclusions based on such data.

As with any empirical research, data accuracy is an important consideration, and this appears in this thesis as well, as discussed in Chapter 4 Section 4.2 and Chapter 7 Subsection 7.3.1. In many ways it is the geographical specificity of the data discussed above that is a considerable strength. However, the reader should consider the distinction between specificity and accuracy. In general GPS location tools are fairly reliable but caution must be exercised in labelling these as infallible. There is evidence for example that a major limitation to GPS is the inability for receivers to determine their position indoors, underground, under dense tree coverage, between large buildings in 'urban canyons,' and anywhere else where a solid object obstructs the view of the sky (Zandbergen and Barbeau, 2011). Yet any VGI relies on users pinning incidents with spatial accuracy. Data sets that use sensing or satellite imagery such as Street View or ambient population estimation only reflect the exact state of affairs at the moment that the information was captured. Places change quickly and this needs to be recognised in studies using 'point-in-time' data sets. The temporal accuracy of VGI datasets relating to events is also of concern. Do people report events in real time? If they do not, what is the implication of using the time of report as the estimated time of the incident?

It is also important to consider the ethical implications of the use and potential misuse of the types of datasets reported here. In our increasingly technology savvy society the use of mobile phone apps, GPS tracking and on-line

participation is on the rise. It is conceivable and indeed likely that those that 'volunteer' information are not necessarily aware that this might enable others to discover more about individual actions and routines. Chapter 4 detailed an exercise where I combined two large data sets and was able to make inferences about individuals in terms of gender and apply that to the reporting activity patterns from a different data set. Presumably, scraping data from many different information sources could enable researchers to build up fairly detailed pictures of the lives of distinct individuals. Researchers, therefore, have an ethical duty to be sensitive to these possibilities. Individuals should always be informed of the type of data they are providing and the conditions for its use. For example, it was made very clear to users of the mobile phone app described in Chapter 7 that a GPS location and time would be attached to their reports; it was also made clear that published results would never enable the identification of individuals as detailed in Chapter 7, Section 7.4. These ethical considerations are important to keep in mind when proposing new modes of data collection about people's everyday activities.

There are further ethical issues to consider around

While these are some limitations and issues to consider when using the approach presented in this thesis, they do not take away from some of the interesting findings which emerged. The next section (Section 9.2) will serve to summarise these, and continue a detailed discussion of some of the most interesting results.

9.2 Summary of findings

While readers must keep in mind the limitations above, results from this thesis illustrate that new types of data provide a way to gain new insight into concepts around perception of crime and place. Table 9.1 shows a summary of the advantages and limitations of the two main approaches presented in this thesis: using openly available crowdsourced data, and using mobile technologies to collect data. Table 9.2 lists the hypotheses that each data set was used to test, and the outcomes put forward in this thesis.

Table 9.1: Summary of novel data collection approaches in this thesis

Summary of novel data collection approaches in this thesis

Bespoke app to collect data for research (FOCApp)		Crowdsourced VGI available online (FMS)	
Advantages	Limitations	Advantages	Limitations
<ul style="list-style-type: none"> • Researcher has a say in the questions asked and data collected • Can make it fit with research design • Flexibility to change to fit specific study needs 	<ul style="list-style-type: none"> • Difficult to increase participation • Sampling bias introduced by requiring technology literacy from participants 	<ul style="list-style-type: none"> • Easy and cheap to collect • Covers large areas spatially(whole city, whole country) and can have large temporal reach (years) • Many participants, and therefore lots of data, allows for slicing into small groups for analysis 	<ul style="list-style-type: none"> • Many assumptions about the data need to be made to be used for research • Researcher has no say in the data that gets collected • Data quality issues require data cleaning • Sampling bias appears inherent in this data

Table 9.2: Summary of novel data collection approaches in this thesis (contd.)**Summary of novel data collection approaches in this thesis (contd.)**

Bespoke app to collect data for research (FOCApp)		Crowdsourced VGI available online (FMS)	
Hypotheses tested in thesis	Falsified?	Hypotheses tested in thesis	Falsified?
Fear of crime varies within people over time	No	Spatial and temporal information associated with this data can be used to represent place and time of people's experiences	No
People are more likely to report higher levels of worry after dark	No	More problem reporting via FMS occurs in neighbourhoods with higher willingness to intervene scores	No
People are more likely to report higher levels of worry in areas they are not familiar with	No	Drop in daytime reporting (compared to night reporting) is associated with higher burglary rates	No
Women report higher fear of crime using FOCApp than men	Yes	Complaints about environmental issues reflect observed instances of these issues collected using Systematic Social Observation	Yes
People who have experienced previous victimisation report higher fear of crime using FOCApp	Yes	Complaints about environmental issues reflect perceived instances of these issues collected using questionnaires	Yes
		Higher rates of complaints about environmental anti-social behaviour (vs other issues) is associated with increased levels of fear of crime in a neighbourhood	No
		Men and women report different issues using FMS	No

Evidently, both methods have advantages and disadvantages, but both serve to add valuable empirical data to contribute towards learning about people's subjective perceptions of crime and place, and their behaviour during their routine activities. Indeed, while exploring these data, within this thesis I have uncovered interesting findings about perceptions and routine activity patterns. I present here a review of my research questions and findings, after which I further detail the most interesting findings below

- Does the crowdsourced data identify neighbourhoods with higher levels of willingness to intervene?
 - Yes, it does reflect this (Chapter 5, Section 5.3).
- Does short-term absence of active guardians (measured with crowdsourced data) show a negative relationship with crime?
 - Yes and this is an effect that is not mirrored when looking simply at population change within the day (Chapter 5, Section 5.4).
- Does this data reflect perceived levels of disorder?
 - No, it shows something distinct to what is captured by questionnaires about perceived levels of disorder (Chapter 6, Section 6.1).
- Does this data reflect observed levels of disorder?
 - No, while it does correlate with observed instances of disorder measured using Systematic Social Observation, there is a filter applied whereby not all observed instances of disorder are reported, only those which people consider to be an issue (Chapter 6, Section 6.1)
- What is the link between fear of crime and experienced signal disorder measured using this new data?
 - There is a positive relationship between the ratio of reports about signal disorder and increased levels of fear of crime across London neighbourhoods (Chapter 6, Section 6.2)

- Do opportunities to encounter disorder vary in place and time?
 - Reported disorder shows significant clustering which varies across different times of the day (Chapter 6, Section 6.3)
- Do experiences with disorder vary between different groups?
 - Variation in reporting between genders has been observed and raises questions about different routine activity patterns leading to different experiences (Chapter 6, Section 6.4)
- Does fear of crime vary within an individual?
 - Yes, and also between individuals, however not along the line of static demographic characteristics at least when measured according to the situational approach employed in this thesis (Chapter 8, Section 8.3)
- What are covariates of fear of crime?
 - Whether the person was in an area they were familiar with or not, and whether the report was made during hours of darkness or in the day-time were the only significant covariates of fear of crime measured using FOCAApp. However, differences between people also emerged as significant, which implies that person-level characteristics remain important (Chapter 8, Section 8.4)

By answering these questions, this thesis has contributed new insight into the small scale, dynamic variation in peoples experiences with fear of crime, signal disorders, and also in the presence of active capable guardians in neighbourhoods. Section 9.3 will now highlight some of the most interesting findings and discuss them further in the following section.

9.3 Discussion of new insight gained

The first finding I would like to highlight is the support for within-person variation in fear of crime illustrated in Chapter 8. This is interesting because it means

that there is an important layer to fear of crime that is not captured by cross-sectional surveys, that measure people's fear of crime at one point in time. Instead, people experience fear infrequently and actually go about their lives mostly not at all worried about crime. However, there are certain situational factors that evoke fear. In this thesis I have identified two dynamic variables, associated with fear of crime. These are whether it was dark or daytime, and whether the participant was outside their area of familiarity (Chapter 8, Section 8.4). Yet there are many other situational variables that would be interesting to explore further. With more data, comparisons with signs of reported disorder through complaints could be made (Chapter 6, Section 6.3). Also fear of crime hotspots could be created, and compared against crime hotspots of different crime types, in particular, signal crimes as well.

Finding situational variation in fear of crime within people highlights that it is at least partly a function of people's everyday routine activities. The significance of individual effects (Chapter 8, Section 8.4) is also important however, and implies an interaction between people's baseline levels of fear and their reaction to the environment. For example, fear is probably easier induced in people with certain characteristics, whether these are static or fluid characteristics. These nuances could be further explored with more intense data collection using the FOCApp method, targeting groups which are hypothesised to have such different propensities for experiencing fear of crime.

The above ties in with the finding of between group variation in what categories of environmental issues were reported using FMS (Chapter 6, Section 6.4). I found a relationship between gender and reporting in different categories. One possible explanation for this is that different genders actually attend to different things in the environment, as suggested by Innes (2014). This is one avenue for exploration. However it is also possible to consider the difference in activity pattern that people might have. For example, in London, men and women do show different travel behaviour. Between 2005/6 and 2014/15 changes in usage of certain transport modes differ by gender (Transport for London, 2015). For example, men cycle more than women, while women walk more than men. Also In terms of trip rates (the average number of trips made

per person per day), women make the highest average number of trips per day (Transport for London, 2015). Such differences in travel activity patterns, for example, could potentially explain some of the variation in exposure to instances of disorder in the environment, or to experiencing fear of crime. This presents an interesting avenue for future work to explore grouping people according to activity patterns, to identify groups with meaningful differences. It can also be interesting to explore grouping people based on activity patterns rather than demographic differences based on this finding.

And finally, another interesting insight I would like to highlight is that the crucial time when signals of disorder affect the people perceiving them, and interpreting them as signals, is at the time when they are seen. It is when the signal is encountered, rather than at the time when the creation of the signal is taking place (for example the time when the graffiti is painted, or when the street drinking occurs) that the potential for someone to experience fear of crime is created. In Chapter 6, Section 6.3 results indicate that people encounter signs of disorder when they enter a space that has signals left behind from a previous usage of that space. For example, in the early morning when going to work, a person walks through an area where street drinking had happened the night before, and sees a signal, and perhaps might experience fear of crime. It is not in the evening time when the street drinking takes place that this happens, but actually in the morning. It might be that they then draw conclusions about the night-time use of that area, and project the fear into that time. In any case, this finding has implications for prevention approaches, as it points out that the most beneficial situational intervention should focus not on the night time activity, but rather the signs left behind in the daytime, when the person encounters those signals.

Overall there are many interesting insights gained in this thesis (for example see Chapter 5, Section 5.4, Chapter 6 Section 6.3 and 6.4, 7 Section 7.3.2, and Chapter 8, Sections 8.3 and 8.4), and these serve to illustrate the potential impact of using crowdsourced data. By utilising the wealth of information in already available data online, or by developing bespoke surveys applied to new technologies, new data can be attained to help explore situational features of

perception of crime and place, and the more subjective elements of people's routine activities, and how these vary in time and space.

The results from this thesis illustrate potential implications for scholarly work. The theories of spatial criminology discussed in Chapter 2, Section 2.1, such as routine activities theory, rational choice theory, and crime pattern theory have not often been applied to the study of subjective perception of crime and place, and this thesis provides a template for that to be carried out in the future. On the other hand, ecological models of crime have considered subjective perceptions, but could utilise similar approaches of applying theoretical frameworks to contextualise the biases inherent in large data. For example, while it is recognised that Google Street View can be and is being used systematically to code a variety of urban street scenes (e.g.: see Odgers et al. (2012)), it is interpreted as lacking investigator control and SSO precision (Sampson, 2013). Instead, crowdsourced sources of SSO, such as FMS could be considered a new form of SSO, carried out not by 'objective experts', but those very people affected by disorder, filtering their subjective perceptions into the data as well.

9.4 Future work

It is hoped that this thesis inspires future work that would focus on using crowdsourced data to explore criminological concepts, and take advantage not only of the attached spatial and temporal information, but also the detail provided with these data. This allows exploration of what such data can be understood to represent, and how they can be applied to further our understanding of perception of crime and place. While some avenues for future work is mentioned throughout, this section hopes to summarise some possible ways to take the approach of this thesis forward, or to build on some of the findings within.

As Chapter 8 Section 8.3 illustrated, the FOCApp research tool is capable of collecting data that reflects spatial and temporal variation in people's experiences of fear of crime as they go about their routine activities. With further data collection, more environmental correlates of fear could be identified, to aid prevention approaches and research. Future studies could utilise this data collection method. To facilitate this, the code has been released for FOCApp on

GitHub in order to download and edit, and to set up with any researcher's own database for data collection. It is advised that any researcher first consults with their organisation's ethics department before use.

Building further on this data collection tool, future research could also include other modes of sensing into the data collected. One example is to use galvanic skin response measurement to track people's levels of arousal as they move about an environment (Warr). This has been done to study people's emotional reactions along a certain route (Hogertz, 2010), or across a city (Nold, 2004). This approach could be combined with the measurement tool described in Chapter 7, to gain further insight into fear of crime.

Sensing methodologies could also be employed to learn more about people's experiences with signal disorders as well. For example, found between-group differences in perception of disorder. One potential explanation for this came from interview evidence from Innes (2014) that men and women attend to different things in the environment. Future work exploring this could utilise sensors such as an ambient eye tracker. This is a pair of goggles that participants can wear while moving about in an environment, and it records what people fixate on with their eyes (Cheng, 2014). Such a tool could be used to look for systematic differences between groups in what they notice and focus on in their environments.

Another interesting finding to build upon is that while situational factors were significant predictors of increased fear, the analysis presented in Chapter 8 also demonstrated the significance of between-person variation. Evidently, people bring with them some propensity to experience fear of crime. Traditionally this has been explored with the social structure variables, but it seems that those did not explain the differences found in this analysis of the data collected about fear of crime experiences longitudinally. It is possible that these individual differences are also linked to people's routine activities. For example, Chapter 8, Section 8.5.2 presented a subgroup of Revenue Protection Inspectors, who by virtue of their routine activities during their work, were exposed to more instances when they could experience fear of crime. Based on their work around the frequency and intensity based questions, for example, Gray et al. (2011)

group people into different categories, who would all require different types of interventions. Similarly, Jackson and Gray group people based on their states of worry and their actions of taking precautions and the extent to which that affects their quality of life. It would be interesting to build upon this and look at creating groups based on more 'high risk' routine activities, experiences with crime as well as fear of crime. It is possible to use clustering techniques, and build on Crime Pattern Theory (Brantingham and Brantingham, 1993) to group people based on their activity patterns, and it would be interesting to compare these groups in levels of fear of crime, using both new and traditional measures.

Finally, as mentioned in Chapter 4 Section 4.1, versions of Fix my street are available for many countries around the world. Future collaborative work with academics from other cities or countries could take place by comparing the reporting patterns of people from these different areas, highlighting further on a large scope the differences between different groups in their experiences with disorder during their routine activities.

9.5 Implications for policy and practice

This thesis offers a template for collecting data about when and where people experience fear of crime. As discussed in Chapter 2, fear of crime is something that affects many people's daily lives, reducing the quality of life, and carrying with it many negative consequences. To map it dynamically in place and time facilitates identification of micro-level hotspots both spatially and temporally to inform situation-based interventions to tackle fear of crime. Similarly, instances of disorder are something that many local authorities want to target, and by finding out when and where they are encountered by the people who perceive them to be a problem, and who are potentially most affected by them, would be beneficial to councils. And also if openly available crowdsourced data can be used to identify areas of fluctuating active guardianship, such information can be used to identify temporarily increased crime risk. This can be used to highlight times and specific places that would most benefit from interventions.

While reassurance policing and community policing has shown benefits in comforting residents, more and more cuts means fewer police resources

to fulfil these roles. Therefore if openly available data can aid in identifying areas of increased risk due to reduced guardianship (Chapter 5, Section 5.4), or can collaborate with partners, such as local authorities to remove signs of low level disorder before the people who are affected by it in negative way see them (Chapter 6, Section 6.3), this could contribute to cost effective targeting of their limited resources. Further, by identifying in place and time on a micro-level when fear or crime is at its highest (Chapter 8, Section 8.3), and targeting these policing initiatives to those times and places, these limited resources could be applied most effectively. Of course, the limitations discussed in relation to slanting services towards super-users should be kept in mind.

Finally as demonstrated in Chapter 8, Section 8.5, if used in a targeted way, such data collection could be used to highlight areas where under-reported crimes might be occurring. Using the example of homophobic hate crime illustrated that many barriers to reporting could be eliminated by asking people to report their own subjective perceptions and experiences. However, such approach faces difficulty in convincing participants (and indeed being able to assure them) that their reporting will be used to drive action, and to attempt to diffuse their everyday encounters with fear of crime.

9.6 Final summary

This chapter has served to summarise the key findings and contributions of this thesis. Section 9.1 emphasised that although many new insights are gained by applying crowdsourced data about people's routine activities and their behaviour and perception as they go about them, there are limitations in these data that must be kept in mind. Then Section 9.2. provided a general summary of the findings throughout the thesis, with Section 9.3 detailing some interesting findings and their implications. Section 9.4 discusses some potential avenues of future work inspired by this thesis, and Section 9.5 detailed potential applications of the research to policy and practice.

Overall, this thesis hoped to illustrate that by applying an environmental framework to the study of perception of crime and place, and mapping out people's behaviour and experiences during their routine activities through the new

data sources, I have gained new insight into the topics of active guardianship, signal disorders, and fear of crime. The situational approach to the study of subjective perceptions remains an area for exploration, and hopefully, throughout this thesis, I have managed to demonstrate some approaches to collecting new types of data to facilitate this in the future.

With the discussion in this thesis I aim to contribute to the growing debate around using such new types of data, specifically around the challenges involved with 'taming' such data. (Williams et al., 2016) emphasize in their discussion the importance of filtering out the noise and transforming content to serve research needs. I hope that this thesis serves as an example of theory driven data collection and interpretation, transformation and analysis. As discussed in Chapter 3, Section 3.1, commonly in prior uses of such new forms of data, their bias (eg: unequal participation) presents an issue. However by framing the study of such data so that they represent peoples subjective experiences in their environments, this bias can be used to understand these data in a more nuanced way. Using this interpretation could caution practitioners who might act on such data to consider not only where reports are coming from, but also why, potentially mitigating against slanting of services towards those who are more vocal about an issue, neglecting others who might be in equal need, but without access to participation in these forums.

Further, I hope to also have supported the thesis put forward by (Housley et al., 2014) that the boundaries of social science research practice are becoming more porous, with social scientific knowledge production potentially becoming more public. Future work building on crowdsourcing could move further down the scale, and lead to the emergence of citizen social science within criminology Housley et al. (2014). There are ethical concerns around the use of such data as a form of surveillance of people, however there is also a possibility here to instead involve people, not just in data generation, but in the interpretation and utilisation of such data. Future research could move further up the ladder of participatory social science, away from people as sensors, towards people involved in the knowledge production and implementation Haklay (2015).

The use of innovative data sets in crime related research will inevitably bloom over the next decade. This should rightly happen, as these data sets offer great promise in advancing our understanding of crime problems. Throughout this thesis, I hope to assert that this is particularly true in research that examines micro-level relationships between crime and place. Whilst recorded crime data and traditional socio-demographic and population data have offered many research opportunities, to study the micro-level interactions between what people do all day in what place and how they experience threats and perceive safety, the only truly valid source of data comes from tracking the people themselves in their environment.

The possibilities offered by the collection and analysis of innovative datasets will continue to grow. Geo-located Twitter data enables the mapping of a new social dimension onto space; it should soon be possible to infer more about the nature of communities with distinct types of crime problem (Kim and Bowers, 2017). VGI data will help us pinpoint vulnerabilities in people's everyday lives that should ultimately help us protect high-risk groups. Better estimation of the ambient on street population should assist with understanding the optimal conditions for offences such as street robbery (Tompson, 2016). 360-degree digital camera shots should assist with the micro-level assessment of the safety of the current environmental design. Attaching physiological sensors to willing participants to examine physical reactions to situations will provide a new angle on methods of making people feel safe. Tracking police car movement should assist in locating communities that are less frequently visited than they should be (Davis and Bowers, 2017). The list goes on. There is no doubt that the increasing availability of new data sets will lead to fertile new research in environmental criminology and ultimately make people feel safer in their everyday lives.

Overall this thesis hopes to serve as a guideline and motivation for the application of novel approaches to data collection to advance research in the field of criminology by adding detailed insight and empirical support to a situational approach for studying the perception of crime and place.

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