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## **Exploring Spatial Patterns of Guardianship Through Civic Technology Platforms**

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### **Abstract:**

Civic technologies levy advances in digital tools to promote civic engagement, giving people a voice to participate in public decision making. While democratising participation, the use of such civic tech also leaves behind a digital trace of the behaviour of its users. This paper uses such a digital trace to explore spatial patterns in active guardianship of public space. Through mapping people's participation in a platform for reporting neighbourhood concerns (a form of digitally enabled guardianship), the spatial range of guardianship is unpacked using exploratory spatial data analysis. Typologies for guardianship behaviour are then created using k-means clustering. Results provide an insight into the heterogeneity of spatial behaviour of different groups of guardians outside the home environment. Guardians appear to not be limited to activity within a neighbourhood, and instead cover a larger awareness space with nodes and paths, and also show distinct patterns, indicating heterogeneity in guardianship patterns. Recommendations are made to consider operationalising guardians as heterogeneous, and active in their entire activity space, rather than homogeneous groups assigned as crime prevention forces to a residential area.

**Key words:** Guardianship, Civil tech, Crowdsourcing, Spatial patterns, Neighbourhood

**Declaration:** This work is original and has not been published elsewhere

## Introduction

Digital technologies designed for enabling citizens to hold governments to account are proliferating at a steady rate around the world (Rumbul, 2015). Something can be considered civic tech, if it acts to leverage digital tools to improve democratic governance towards more transparency, inclusion, and participatory outcomes. This covers a range of activities, from ‘civic hackathons’, which are participatory events for prototyping of innovative services through collaboration between citizens and engineers towards addressing social issues (Shiramatsu, Tossavainen, Ozono, & Shintani, 2015), to citizens who want information about government housing policies but lack the mobility to visit a council office being able to request electronic copies to their homes (Rumbul, 2015). The growth in adoption of these civic technologies has the potential to invigorate citizen engagement and broaden public debate, while also leaving behind digital footprints of the active roles people take in their communities. These developments provide researchers with unprecedented insight into social processes relevant to the study of crime (Solymosi & Bowers, 2018). When the data thus generated contain a geographic component, they can be used to explore spatial patterns in people’s activities. This paper makes use of such data to explore spatial patterns in the guardianship of public space.

Guardianship is a social process where people protect an environment by blocking crime opportunities (Cohen & Felson, 1979). For example, people who stay at home during the daytime might act as guardians protecting their homes from burglary (Hollis-Peel, Reynald, van Bavel, Elffers, & Welsh, 2011). Further, it is important for a guardian not only to be present, but also have capacity and willingness to intervene (Reynald, 2009). This form of *active* guardianship has been explored relevant to guardianship inside the home, but has not yet been applied to guardianship explored in public space.

Data from civic technology platforms can be used to understand how people engage in a form of digitally enabled guardianship. The spatial component of these data allows the mapping of guardians' activity spaces and to explore guardianship typologies. This has been done in prior work for offenders and victims, but not guardians. Instead, spatial exploration of guardianship has mostly been approached by operationalising guardianship in public places as an attribute of neighbourhoods. Traditionally, some spatial unit of analysis, such as a census block is attributed a guardianship score based on residents' answers to survey questionnaires about willingness to intervene, or collective efficacy. However, it is possible that individuals can act as guardians outside their census tract that they live in. Mapping individual-level guardianship in public spaces allows commentary on how this behaviour relates to traditional approaches to analysis of guardianship.

The contribution of this paper therefore is twofold. First, exploratory spatial data analysis is used to map individual-level spatial patterns in guardianship behaviour, with reference to some measure of neighbourhood. Second, based on the spatial patterns of guardianship behaviour, guardianship typologies are created to differentiate between different types of guardians who may have different types of effects on crime opportunities in different areas. Results highlight diversity in people's engagement with guarding their physical environments which means there should be consideration of individual guardians and their reach beyond their home neighbourhoods and that guardians, even active guardians, should not be treated as one homogeneous group.

## **Theoretical Background**

### *Civic Engagement and the Democratisation of Data*

People's participation in online activities leaves behind a digital trace, available to researchers to gain insight into their everyday experiences. For example, protesters are making use of new technologies of video streaming to engage more people with their cause

(Melgaco, 2016). In this way, protests are not only being registered but also broadcast in real-time (Melgaco, 2016), allowing for researchers to tap into these with little cost, and observe events from across the world. Similarly, smartphone applications are being used to record people's experiences with outcomes such as mental health (Bakolis et al., 2018) and fear of crime (Solymosi, Bowers, & Fujiyama, 2015). Data from Twitter are commonly used for example to create a measure of 'broken windows' using a text classification procedure (Williams, Burnap, & Sloan, 2016), explore activity patterns to estimate crime risk (Malleon & Andresen, 2015), or to explore the relationship between citizens and the police (Lee, McCormick, Spiro, & Cesare, 2015).

The rise of digitally engaged citizens has been facilitated through the emergence of 'civic tech'. Civic tech, short for civic technology, concentrates on how technology shapes how communities govern, organize, serve, and identify matters of concern (Boehner & DiSalvo, 2016). The connectivity of the internet has the potential to democratise a whole spectrum of previously complex or oblique processes through increased access, functionality and relative anonymity.

Data resulting from people's participation from such civic engagement platforms are interesting not only because of the ease of access, and the new insight gained, but also because of the potential for democratisation of data collection. Participatory map-making, for example, can be seen as a way to raise awareness (O'Connor, 2010), and as a way for people who are often seen as passively "being mapped" to "counter-map", expressing their own experiences, and as such "resisting the power of the state" (Wood, 2010). Although these participatory exercises still take place within the paradigm of the authoritative institutions, they nevertheless 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.

This is the case with civic tech platforms designed to report neighbourhood issues. It provides a forum for people to report the issues they want their local authority to address, in a way that is easy to use, and is immediately passed on to the relevant local authority, while also providing a public platform to monitor whether or not the issue has been addressed, and to hold them to account. Additionally as allowing citizens to monitor whether their issues are being addressed, the platform also creates a catalogue of issues reported. Such data has been used to represent measures of 'broken windows' (O'Brien, Sampson, & Winship, 2015) and signal disorder (Solymosi, Bowers, & Fujiyama, 2017). But besides representing where potholes and instances of graffiti are present in a neighbourhood, this participation also shows where the people reporting go, and actively monitor their environments. The innovation of this paper is to consider this element of the data generated, and consider not *what* is being reported, but the *who* that is doing the reporting. In this way, such data can provide insight into the spatial patterns of behaviour of capable guardians.

### *Guardianship and Crime Prevention*

The concept of guardianship is an important feature of routine activities theory, which posits that for a crime event to take place, there are three required elements: the presence of a motivated offender, the presence of a suitable target, and the absence of a capable guardian (Cohen & Felson, 1979). A vast body of literature has since been dedicated to unpacking this concept of capable guardianship. Much of it has focused on developing a clear definition of guardianship, what the guardianship process entails, and how exactly guardianship occurs (Hollis-Peel et al., 2011). The concept of *active* guardianship proposes a four-stage model of guardianship intensity, which describes guardians on a spectrum from being invisible, to being available, capable, and willing to actively intervene (Reynald, 2009). This approach

has been validated using theoretical field tests and natural experiments, considering people's guardianship behaviour while in the home.

However measurement of guardianship in public spaces has not yet incorporated this theoretical innovation of guardianship in action into its operationalisation. Instead, population estimates are considered to represent victims, offenders, and guardians in one crowd. Hipp, Bates, Lichman and Smyth (2018) have engaged with this issue by conceptualising guardians as a homogeneous subset of the ambient population. However this is not a direct measure of guardians, and does not account for availability, capability, and willingness to intervene of the individual guardians.

When guardianship is measured outside the home, it is normally conceptualized as a feature of some spatial unit of analysis such as neighbourhood (Bernasco & Nieuwbeerta, 2005; Hollis-Peel et al., 2011; Reynald, 2011), street segment (Moir, Stewart, Reynald, & Hart, 2017), or even bus shelter (Newton & Bowers, 2007). However, attributing guardianship as a parameter of a spatial unit can mask variation in individual guardians' behaviour by not considering the possible mobility of guardians within and between these areas. To account for such variation, it might be meaningful to consider the spatial patterns of guardians themselves, in the same way that the spatial patterns of offenders have been considered by crime pattern theory.

#### *Crime Pattern Theory and Guardianship Activity Patterns*

It is important to consider the routine activities of guardians to understand their ability to act as *active* guardians. For example, micro-activities within the home mean that even while at home, people can act as guardians only when their routine activities allowed them to practice surveillance of their neighbourhood (Moir, 2016). If a resident's kitchen counter faces a window overlooking the street, then they are likely to be able to act as guardians over the

street while they are preparing lunch or dinner, but less so when they are in their study, or bedroom (Moir, 2016).

While evidently relevant, the activity patterns of guardians outside their homes are much less explored. One approach to frame the effect of routine activities outside the home on guardianship behaviour is to consider crime pattern theory. Individuals have a range of routine daily activities. Usually these occur in different nodes of activity such as home, work, school, shopping, entertainment or time with friends, and along the normal pathways between these nodes (Brantingham & Brantingham, 2008). According to the geometry of crime, targets for offenders vary as awareness of opportunities to commit crimes vary in time and space (Brantingham & Brantingham, 2008). While mostly applied to the motivated offenders and the suitable targets element of the crime triangle (Felson, Clarke, & Webb, 1998), this can apply to opportunities for guardianship as well.

Applying this framework to study behaviour patterns within the home, Moir (2016) developed typologies of guardians in order to understand how often residents monitor their street and the differences between residents in this type of crime control behaviour. Forming these typologies contributes significantly to developing active guardianship model, because it considers the importance of the predisposition of possible guardians, and provides further insight into the guardianship process. However, this work was still limited to activity within the home, and does not take into account guardians' entire activity space. By unpacking the macro spatial patterns associated with guardianship in public space, it would be possible to conceptualise guardianship from a crime pattern perspective, rather than focus on it as a feature associated with a spatial unit such as a neighbourhood, which itself brings about a series of conceptual challenges.

*The Neighbourhood as a Unit of Analysis*



As mentioned above, guardianship is often measured at an aggregate spatial unit of analysis, such as neighbourhood. The theoretical framework of social disorganisation theory for example postulates a link between neighbourhood disorganisation, and guardianship (Bursik, 1988). Guardianship in this instance is operationalised as residents' responses to survey questions designed to measure willingness to intervene, aggregated to produce a score at census tract, or some other measure of neighbourhood. The issue of operationalising neighbourhood is much discussed, for example in relation to the Modifiable Area Unit Problem, where the scale and aggregation of the areal units chosen can affect the outcomes measured (Gerell, 2017; Openshaw, 1984; Weisburd, Bruinsma, & Bernasco, 2009) . There is a whole area of research focusing on the impact of using different area geographies to represent neighbourhoods (Brunton-Smith, Sutherland, & Jackson, 2013; Hipp, 2010a; Manley, Flowerdew, & Steel, 2006; Rengert & Lockwood, 2009; Weisburd et al., 2009; Wikstrom, Ceccato, Hardie, & Treiber, 2010). For example, whether neighbourhood satisfaction covariates were measured at local micro-neighbourhood level, or larger census tract level had an effect on the results, indicating that people consider their immediate environment, rather than the census tract when asked about 'neighbourhood' (Hipp, 2010b)

But a particular challenge for the study of people's activity patterns is to define the limits of 'neighbourhood', as perceived by study participants themselves (Charreire et al., 2016). Community studies highlight the misalignment between administrative area boundaries and capturing the contingent nature of neighbourhood for individual residents (Brunton-Smith et al., 2013; Lupton, 2003). Some approaches to tackling this are to use matrices of social distance to consider connectedness (Hipp, 2010a), to crowdsource the re-drawing of neighbourhood boundaries (Woodruff, 2012) or to use social media data to identify 'digital neighbourhoods' (Anselin & Williams, 2016). These approaches share a reach for new forms of data to aid the reframing of the concept of neighbourhood. However, the granularity of

data afforded by civic tech platforms that promote digitally enabled guardianship allow for the consideration of the activity spaces specifically of guardians, and the extent to which that guardianship awareness space reflects the approach of using administrative boundaries to reflect this.

### *Hypotheses*

This paper addresses the following hypotheses: The awareness space of guardians, and therefore area where they act as guardians through reporting neighbourhood issues, is not limited to neighbourhood as defined by administrative boundaries.

Spatial patterns of guardianship behaviour are not uniform between different guardians; instead, different typologies are likely to exist with differences in routine activities.

## **The Current Study**

### *The Study Area*

The study area covers England, and considers activity on the relevant civic technology platform between January 2011 and January 2015.

### *Data*

The data for this research comes from the online problem reporting tool *fixmystreet.com* (hereon referred to as FMS). FMS exists as both a webpage and a mobile application, and was created to allow people to report issues in their local area efficiently and effectively, as they go about their everyday activities, without getting tied up in the kind of bureaucracy that has historically characterised public services (Rumbul, 2015). Using the website, citizens are able to locate their problem on a map, describe it, and upon submission 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).

The aim of this paper is to consider the movement of active guardians. To ensure the measure reflects this, active guardians were operationalised as the top 1% most active participants of

FMS. These people can be considered consistently and actively monitoring their activity spaces by reporting issues on FMS.

To identify the “super contributors” (Stewart, Lubensky, & Huerta, 2010), the FMS data was subset to first exclude anonymous reporting, leaving a total of 48,064 unique people who left a name with their report, who made a total of 109,780 reports between them. Of these the most active people, the top 1% of contributors were selected, in line with the discussion about the participation inequality (Stewart et al., 2010). From this top 1%, non-people names, which could have been associated with multiple people were removed (for example "customer service centre", or "Local Resident"), resulting in a sample of 415 unique top contributors, who made a total of 27,058 reports (10% of all reports).

Census geography data is also used to answer the questions about the suitability of aggregating guardianship behaviour to neighbourhoods. Earlier, the issue with attributing guardianship as a parameter of a neighbourhood was discussed. Lower Layer Super Output Area (LSOA) is a commonly used geography to represent neighbourhoods designed to improve the reporting of small area statistics in England and Wales with a minimum population of 1,000, maximum of 3,000 and a mean of 1,500 (Office for National Statistics, 2017). It is preferred for research comparability and stability over time, an advantage over administrative boundaries (Sturgis, Brunton-Smith, Kuha, & Jackson, 2014). In this study, the unit of analysis remains the individual guardian, and neighbourhood data is used to create a new variable for the number of neighbourhoods guardians report in, as well as used for the feature engineering part of the analysis.

### *Methods*

The paper will first consider a descriptive analysis of people’s reporting behaviour through exploratory spatial data analysis (ESDA) (Bivand, 2010), to annotate guardianship behaviour in public space with some details, before moving on to describe spatial patterns. This is

followed by creating measures to characterize these spatial patterns, through feature engineering. Feature engineering is an initial step in building machine learning models, where raw data is transformed into meaningful variables, using domain knowledge to choose which data metrics to input as features (Trevino, 2016). Using meaningful features that capture the variability of the data is essential for the algorithm to find all of the naturally-occurring groups (Moro, Cortez, & Rita, 2014). Feature engineering has been used in criminology to identify meaningful features for predicting crime hotspots (Borges et al., 2017). The development of the features used to classify guardians based on their activity patterns will be discussed in detail in the findings, as they were informed by the preliminary data analysis. which are then used to create typologies of guardians' behaviours through clustering analysis.

Finally, cluster analysis is used to create typologies of guardians' behaviours. Cluster analysis is a tool for sample classification, where *ab initio* class discovery (when class labels are not known in advance) leads to meaningful insight. For example, this method has helped create typologies of road traffic collision hotspot to inform road safety campaigning (Anderson, 2009), or to classify street segments based on their longitudinal crime patterns (Curman, Andersen, & Brantingham, 2015). Grouping the data into clusters with similar features is one way of efficiently summarizing the data for further analysis. One of the most widely-used clustering algorithms is *K*-means (Raykov, Boukouvalas, Baig, & Little, 2016). *K*-means assigns all points in the data to clusters around a set of *k* centroids (Adnan, Longley, Singleton, & Brunsdon, 2010).

There are some assumptions that the data must meet in order for *K*-means clustering to be valid, including that the data space is isotropic, linear without outliers, it does not take into account cluster densities, and that the number of groups are known in advance (Raykov et al., 2016). In the case of the FMS data, the assumptions are not violated, and the optimal number

of groups is worked out in advance through the data using the elbow method (Sarstedt & Mooi, 2014).

One issue with unsupervised learning such as clustering, is assessing the validity of the clusters (Şenbabaoğlu, Michailidis, & Li, 2015). Clustering is “good” if observations in the same groups are similar (average distance *within* each cluster are small) and observations in different groups are dissimilar (average distance *between* each cluster are large) (Charrad, Ghazzali, Boiteau, & Niknafs, 2014). Validation measures therefore reflect the compactness, the connectedness and separation of the cluster partitions. The two measures for validation used in this paper are silhouette width and the Dunn index. Silhouette width is the average of each observation’s silhouette value (the distance between each data point, the centroid of the cluster it was assigned to and the closest centroid belonging to another cluster). It essentially measures the degree of confidence in the clustering assignment of a particular observation, with well-clustered observations having values near 1 and poorly clustered observations having values near -1 (Sengupta, 2009). The Dunn Index is the ratio of the smallest distance between observations not in the same cluster to the largest intra-cluster distance (Brock, 2014). Compact clusters that are well separated should have small value for largest within-cluster differences and large values for the smallest between-cluster difference. However, this index is vulnerable to outliers as only two distances are used (Günter & Bunke, 2003).

## **Results**

### *An Insight into Guardianship Behaviour in Public Places*

ESDA results allow an insight into the data, and reveal unequal contribution between the guardians. The number of reports submitted per person varies widely, between just 20 reports by the least prolific, and 863 reports by the most prolific individual (mean = 56, median = 33 standard deviation = 70). This shows a heterogeneity in people’s behaviour where some

guardians are more prolific than others, and possibly act as guardians in more situations, and more frequently than others.

Additionally, the issues about which people report also appear to be heterogeneous. Crime pattern approach to studying offending found that only few offenders commit only one type of crime and frequent offenders engage in a variety of offences (Brantingham & Brantingham, 2008). Similarly, prolific guardians also appear to report guardianship over various topics. Considering all their reports, only 16 of the 415 contributors reported only one type of issue. The other 399 reported issues in more than one category (mean = 6, median = 6, standard deviation = 2, max = 15 (out of possible 27 categories)). Evidently, FMS participants are mostly topic agnostic, and are general guardians of more than just one particular type of issue. Therefore assuming that the presence of any one of these people as equally effective in preventing a crime event might be an inaccurate simplification of guardianship behaviour.

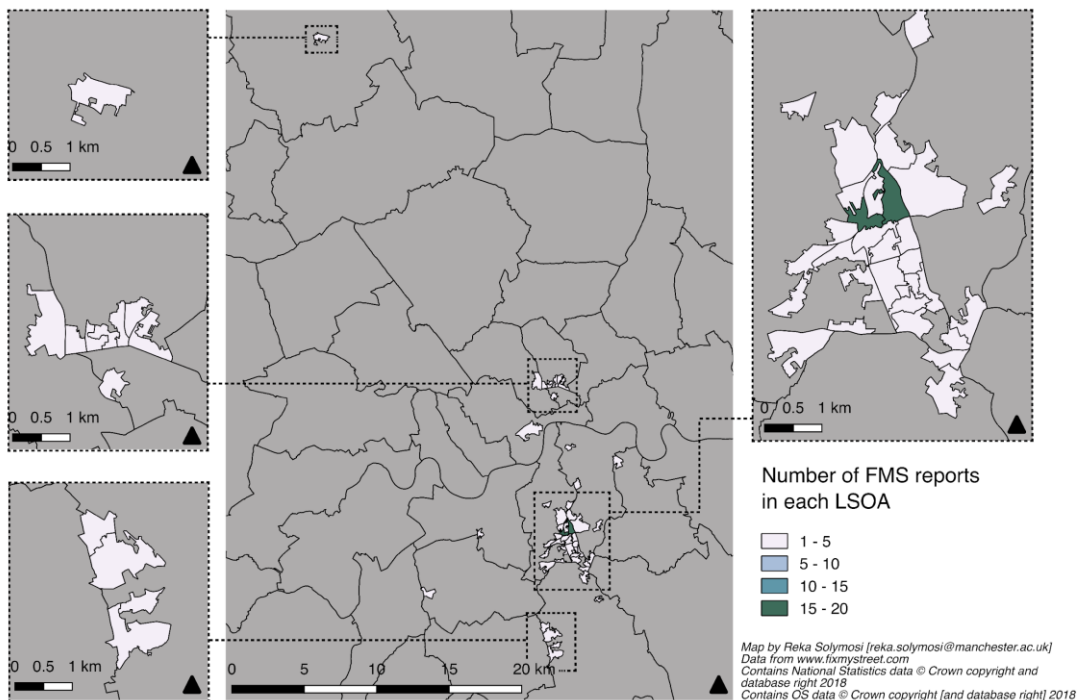
While heterogeneity of topics people report, and in volume of reporting offers insight into guardianship behaviour, to answer the questions about the spatial patterns, the number of neighbourhoods in which people report is considered. There were only six people who reported in only one neighbourhood, fewer than the number of people who reported in only one category. The other 409 contributors all reported in at least two neighbourhoods. Interestingly, the top reporter (person with highest number of reports) was not the person who reported in the highest number of neighbourhoods. The average number of neighbourhoods in which people reported was 17 neighbourhoods (median = 13, standard deviation = 17, maximum = 162), however this is skewed right by some outliers who reported in many more. This result indicates an activity space which does not line up with an administrative boundary definition of neighbourhood. Guardians captured by this measure report in many neighbourhoods, and assigning them as guardians over only the one neighbourhood which

contains their place of residence may not reflect their guardianship potential. This raises some important questions about aggregating guardians to specific spatial units, such as whether this oversimplifies and reduces the range of guardianship behaviour.

Besides descriptive statistics, ESDA comprises of visualisations of the spatial data. Plotting individual maps of reporting activity reveals distinct spatial patterns. For example, many participants seem to make most reports in one or two key LSOAs, with few reports in LSOAs connected to these key ones. This pattern of reporting is characterised by high connectivity between LSOAs where neighbourhoods with many reports can be assumed to contain some sort of activity node for this guardian, and other LSOAs that connect them, which perhaps the guardian travels through, or visits less frequently. This type of spatial range of reports appears to be quite distinct from another group of FMS participants, who seem to report in multiple disconnected places. Figure 1 shows the range of one such participant.

Figure 1: Participant with many far away neighbourhoods

*Spatial range of reporting activity by a prolific participant of FixMyStreet*



This person has multiple clusters of neighbourhoods in which they report, with a few standing out as key nodes, but which are characterised by low connectivity.

It is evident that differences in spatial patterns of behaviour exist, and some participants feel motivated to guard the areas where they frequent, taking ownership of their area possibly in line with social cohesion and collective efficacy interpretations of guardianship. On the other hand, the participant in Figure 1 seems to observe their environment during all travels, and act as a digitally-enabled guardian through reporting on FMS in multiple, disconnected spaces.

The ESDA results point towards heterogeneity in guardianship activity, and in particular in the spatial patterns of issue reporting. It revealed that guardians are not only active within their neighbourhoods, and instead their spatial patterns resemble activity nodes connected by paths, highlighting an awareness space characterised by guardianship activity throughout.

### *Feature engineering*

To answer the research question on whether guardians can be grouped into meaningful typologies based on spatial patterns of reporting, results from the ESDA are used to inform feature engineering. The following features were developed as indicators of different aspects of the spatial pattern of people's reporting behaviour:

- Number of neighbourhoods (LSOAs): According to traditional approaches to conceptualising and operationalising guardianship at neighbourhood level, each participant would be expected to report in only one LSOA. The descriptive analysis has shown that this is not the case. Therefore it can be meaningful to note whether the number of neighbourhoods reported in differs between different types of guardians.
- A connectivity score based on the connectivity of the LSOAs in which reports are made: a connectivity measure can be used to determine whether people report in connected neighbourhoods, or whether they report in multiple disconnected LSOAs.



To calculate this score, a function for testing if the geometries have at least one boundary point in common was used, and the results summed (Bivand & Rundel, 2017).

- The distance between the LSOAs in which reports are made: It is important to know how far reaching a guardian's activity space is. Besides knowing how many neighbourhoods, and how connected they are, it can make a difference how far apart these neighbourhoods are. People who report in areas that are quite far apart can be considered to act as guardians in quite distinct places, possibly places where they go for holiday, or to visit friends, and not just places where they live and work. To be able to consider this dimension of spatial guardianship behaviour, a mean distance value between LSOA polygon centroids was calculated, using geodesic distance on an ellipsoid (Karney, 2013).

Conceptually this process can be understood as an attempt to group guardians along three axes of the spatial behaviour patterns: their range (number of neighbourhoods they guard), compactness (connectivity of the neighbourhoods they guard), and reach (distance between neighbourhoods they guard). All the results were standardised using z-scores, as the values (and therefore their distributions) are sensitive to the unit.

#### *Guardianship Heterogeneity*

An elbow plot was used to determine the optimal number of clusters for the data was four, and k-means clustering was carried out to group the data into four distinct categories. First, it is important to establish whether the clustering is meaningful. One possible outcome from cluster analysis can be that there are no organic clusters in the data; instead, all of the data fall along the continuous feature ranges within one single group (Trevino, 2016). If this is the result, we cannot build meaningful typologies of guardianship behaviour based on spatial patterns identified above. Diagnostic tests help to ascertain whether the groups are

meaningful. As mentioned earlier, one approach is to consider the silhouette widths. The average silhouette width is 0.55, which indicates that a reasonable structure has been found (Kononenko & Kukar, 2007). However some observations in cluster 4 have negative silhouette widths. Negative values indicate that an observation is in the wrong cluster. It is possible to identify these observations and assign them to their “neighbour” cluster, where they are likely to belong. Once these observations have been reclassified, the average silhouette width increases to 0.57. However, the value for the Dunn index score is 0.6. Because this number is below 1, this indicates that the largest within-cluster difference is greater than the smallest between-cluster difference. While this is not an indicator of ‘good’ clustering, it can be put into context by looking at Figure 2. As this value is calculated by only two numbers, it is sensitive to outliers, and it can be seen that there are some outliers in the data, contributing to this low value.

Sensitivity testing with re-running the analysis with  $k = 3$ , and  $k = 5$  further confirms that  $k = 4$  is a reasonable number of clusters. Re-running the analysis with three clusters results in the loss of a meaningfully distinct group from the typology. Revisiting again with five groups however gives worse diagnostic results; the silhouette width drops to below 0.5 (sil width = 0.43) indicating that the structure is weak and could be artificial, and the Dunn index also drops (0.009). The use of five groups does not contribute a new guardianship behaviour pattern to the typology developed with four groups.

These results support the meaningful clustering of guardians into four groups based on the spatial patterns of behaviour. The next section will explore these clusters.

### *Guardianship typologies*

Figures 2 and 3 help visualise the observations along the features, which were used to classify them in the first place. The cluster characteristics will now be used to describe each

typology of guardianship.

Figure 2: 3D scatterplot of features

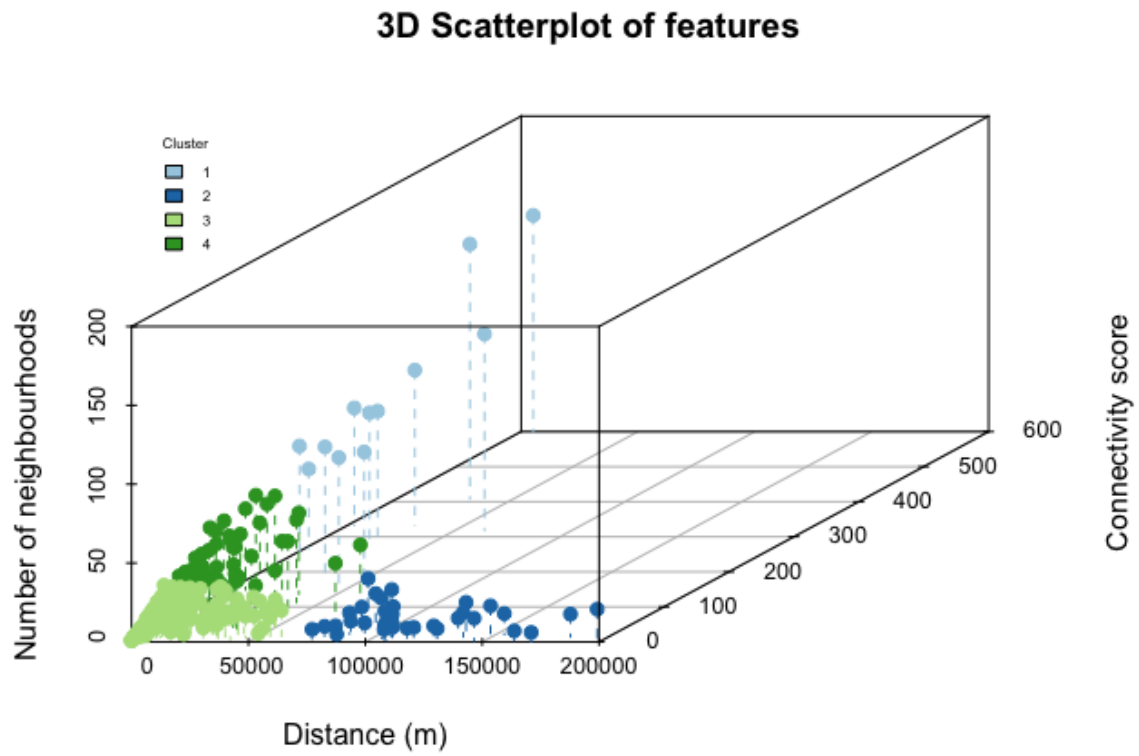
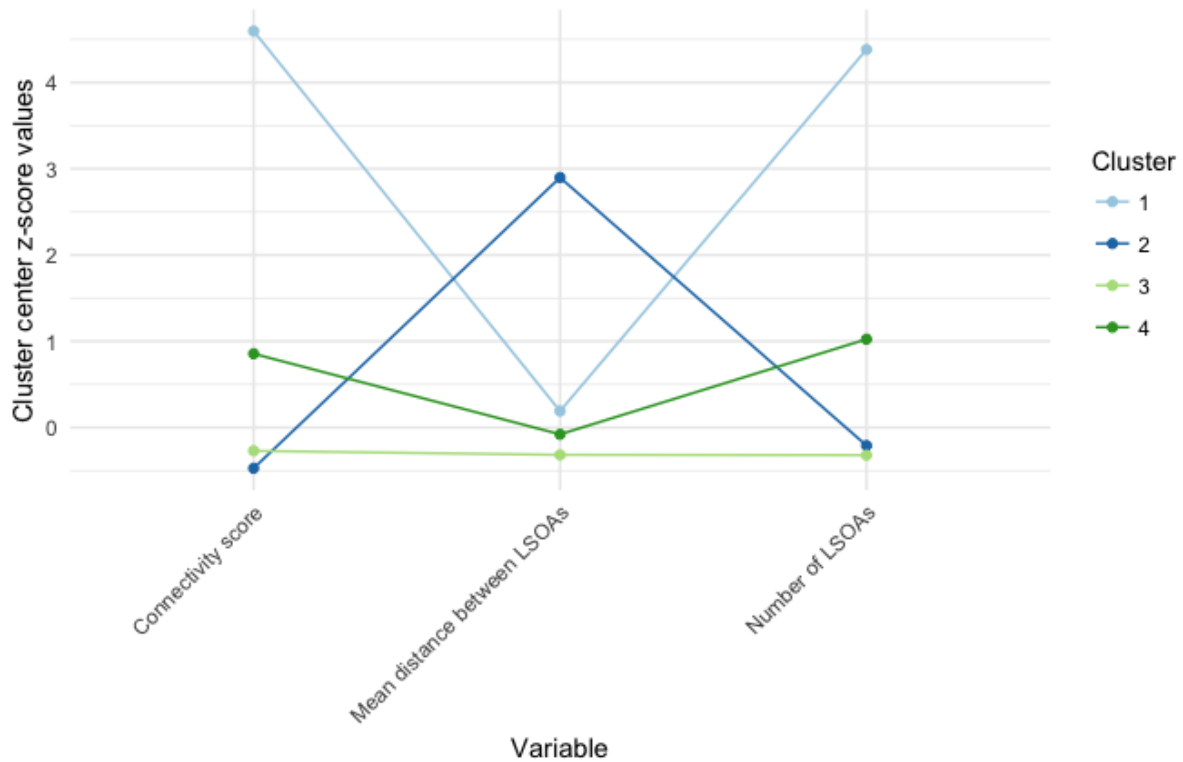


Figure 3: Cluster values for features



*Cluster one* represents people who report in a high number of neighbourhoods that are highly connected, and are close together. This group has the highest connectivity score, and highest number of LSOAs as well, with people making reports in an average of 94 neighbourhoods. The high connectivity score means that these neighbourhoods are clustered together, and this is reaffirmed by the low average distance between neighbourhoods (around 26 kilometres). This group represents *super neighbourhood guardians*, who act as active guardians across the range of their activity space, which covers a large number of neighbourhoods defined by LSOAs.

*Cluster two* is the opposite of cluster one. These guardians report in a low number of neighbourhoods (average of 13) that are not highly connected (lowest score of all clusters), and are far away from one another. The mean distance between the neighbourhoods is 118

kilometres, by far the largest for all clusters. This means that these people anywhere they go, when they encounter something they report it. They are *neighbourhood agnostic guardians* who report any issue they come across, anywhere in their activity space.

*Cluster three* have the highest number of people, representing the modal behaviour of FMS participants. This most common spatial pattern is characterised by consistently low number of neighbourhoods (mean of 11), with relatively low connectivity compared to other groups (higher only than cluster two), but not too far apart (mean distance of 9km). These are the *traditional guardians*, who focus on their areas of familiarity, which is a smaller activity space than other clusters.

Finally, *cluster four* shows patterns similar to cluster one, with high number of neighbourhoods (mean of 34), highly connected, and further apart from one another, but report in not as many neighbourhoods nor as far apart as the super neighbourhood guardians. This behaviour can be understood as a less “extreme” version of cluster one. For example, the average number of neighbourhoods in which members of this cluster report is 35, which is significantly higher than clusters two and three, but just over a third of the number of neighbourhoods reported in by cluster one. Similarly, the connectivity score is much higher than clusters two and three, but significantly lower than cluster one. These guardians can be understood as *large neighbourhood guardians*, as their spatial range is larger than the *traditional guardian* (cluster three) and smaller than the *super neighbourhood guardian* (cluster one) but is characterised by higher connectivity than the *neighbourhood agnostic guardians* (cluster two), representing a cohesive area still.

Table 1 shows more details about each cluster’s scores on the features used to classify them, and Figure 4 shows example maps for each cluster.

Table 1: Cluster details







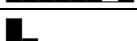
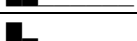




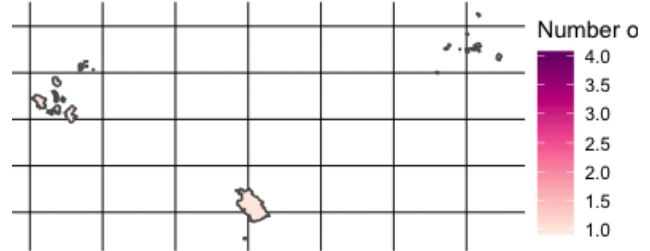
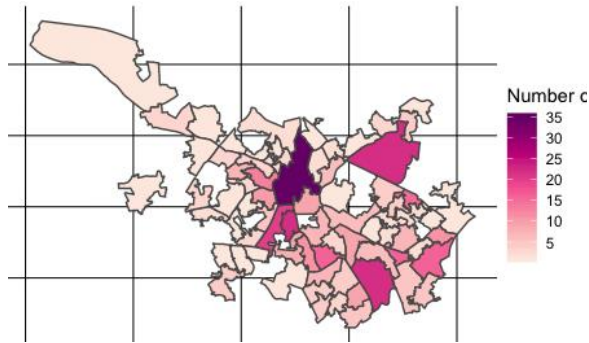
Variable	Cluster	Mean	Standard deviation	Minimum value	Median	Maximum value	Histogram
Number of LSOAs	1	94	32	51	82	162	
	2	13	6	4	12	27	
	3	11	6	1	11	28	
	4	35	11	20	34	56	
Mean distance between LSOAs (m)	1	26224	19501	2442	29018	63238	
	2	117986	30132	77212	108713	196970	
	3	9025	12696	0	3682	60295	
	4	17096	17071	1437	11665	78428	
Connectivity score	1	299	117	166	278	596	
	2	11	13	0	10	64	
	3	23	15	0	20	74	
	4	87	36	26	74	200	

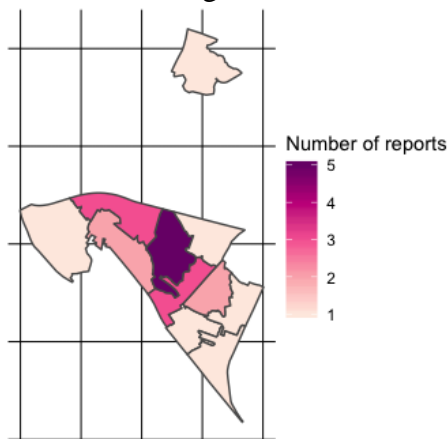
Figure 4: Example maps for each cluster

Cluster 1 – Super neighbourhood guardians

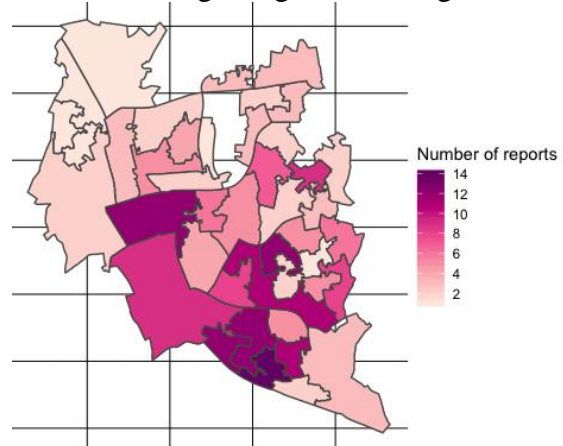
Cluster 2 – Neighbourhood agnostic guardians



Cluster 3 – Traditional guardians



Cluster 4 – Large neighbourhood guardians

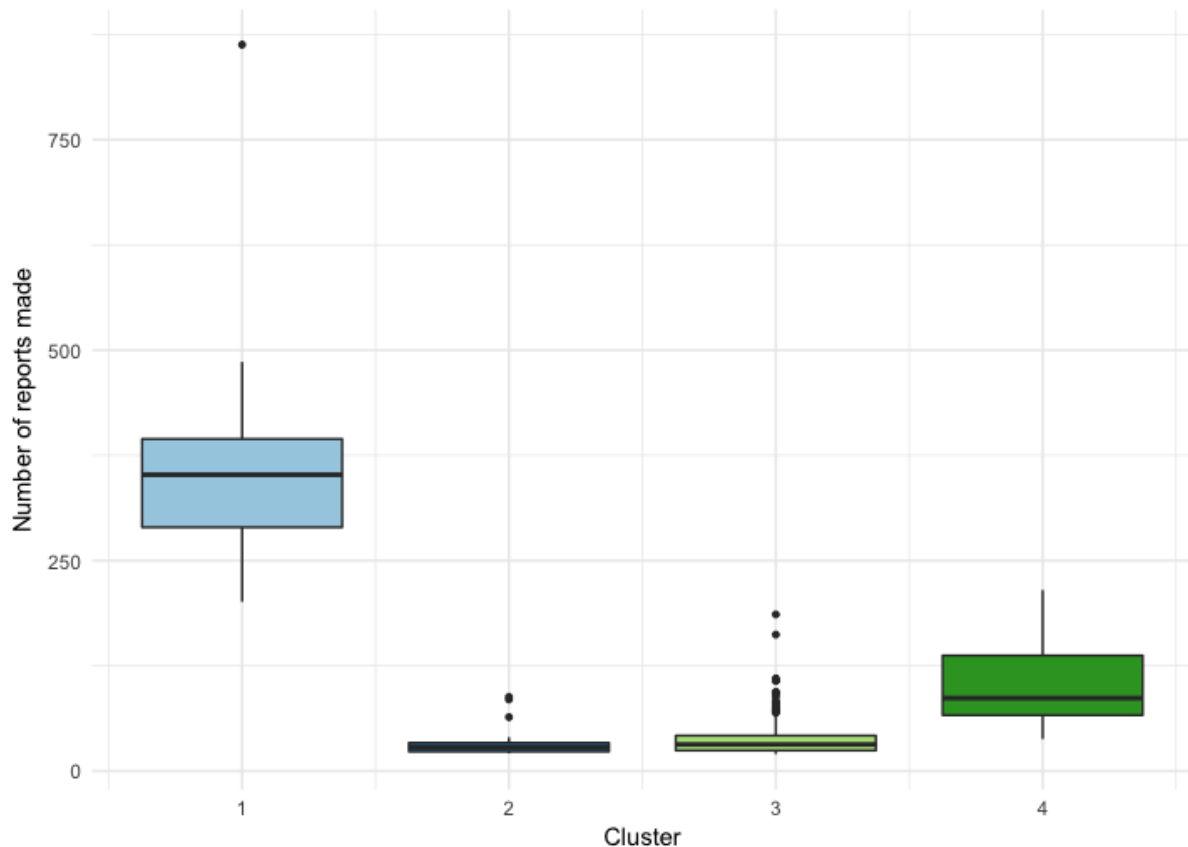


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Data from [www.fixmystreet.com](http://www.fixmystreet.com)

Besides using the features to describe these groups, the characteristics explored during ESDA can also be compared between groups. Across the groups, it could be expected that super neighbourhood guardians are the most prolific reporters, followed by large neighbourhood guardians, whereas the neighbourhood agnostic guardians are least prolific, reporting only when they encounter something that motivates them to report. Indeed, ANOVA results show support for this hypothesis ( $p < 0.001$ ,  $F = 27.29$ , degrees of freedom = 1). A post-hoc pairwise comparison shows that this result is driven by the differences between cluster 1 and

clusters 2, 3, and 4, and also the differences between cluster 4 and clusters 2 and 3. Figure 5 illustrates these comparisons.

Figure 5: Number of FMS reports by cluster



Regarding the diversity of categories that people report in, it might be interesting to explore whether certain guardian types are more heterogeneous in their reporting topics, as well as in their spatial patterns. *Super neighbourhood guardians* (cluster 1) report in more categories than other clusters, possibly due to making more reports allows for reporting in more categories. But the interesting thing to note is the high number of topics reported by *neighbourhood agnostic guardians* (cluster 2). It seems that not only are these people neighbourhood agnostic, they are also more topic agnostic than *traditional guardians* (cluster 3)



The ANOVA in this case does not show a difference between the groups in the number of categories ( $p = 0.124$ ,  $F = 2.372$ , degrees of freedom = 1), so a difference between the diversity of topics in which these guardians report cannot be supported. However, to test the assumption that the neighbourhood agnostic group are “more” topic agnostic than the traditional group, we can subset the data to include only those, and run a Welch two-sample t-test. This shows that there is a significant difference between the number of categories in which the neighbourhood agnostic group report, compared with the traditional guardianship group ( $t = 2.8$ ,  $df = 42.3$ ,  $p\text{-value} = 0.008$ , Cohen’s  $d$  estimate = -0.5 (small)).

### **Discussion**

Brantingham and Brantingham (2008) posit that the process of committing a crime is patterned. Likewise, it seems that the process of intervening as active guardians is similarly patterned. ESDA of civic tech participation for reporting neighbourhood issues showed that guardians operate across an activity space that appears to contain multiple nodes. This is illustrated by the finding that people report in multiple LSOAs, often with a few key LSOAs with many reports (nodes), and others connecting them with fewer ones (paths). The first research question asked whether aggregating guardianship to a spatial unit, such as a neighbourhood is a meaningful way to operationalise guardianship. Issues with defining neighbourhoods were discussed, with particular focus on the discrepancy between administrative geographies, and people’s subjective definitions of neighbourhood. In this instance, if a commonly used operationalisation of neighbourhood (LSOA) were to be used, this would not comprehensively cover these guardians’ awareness space.

To answer the second research question, the homogeneity of guardians’ spatial behaviour was evaluated using clustering. Results grouped guardianship behaviour in public space into four meaningfully distinct groups. This has implications for guardianship research, where caution should be taken treating guardians as a homogeneous group, not only in terms of their

availability and capability to intervene, but also in terms of their spatial patterns of where they may act as capable guardians.

The descriptions of the groups provide an insight into the spatial patterns. One of the groups, labelled *traditional guardians*, can be considered to fit into the framing of a guardian of their neighbourhood. While their idea of a neighbourhood definitely does not correspond with administrative boundaries (they cover on average 9 LSOAs), it is possible that by re-framing the concept of neighbourhood in a way that corresponds to people's own definitions, these guardians can be considered to be active in such spaces. This could be because they feel a sense of ownership and collective efficacy in the neighbourhood, in line with social disorganisation theories that emphasise how collective efficacy at the micro geographic level is relevant and important (Weisburd, Groff, & Yang, 2014) or simply due to them having smaller activity spaces, in line with crime pattern and routine activities theories (Brantingham & Brantingham, 1993).

Other groups support the assumption that active guardians monitor their environments not only in their neighbourhood, but throughout their activity space. This was observed with the *neighbourhood agnostic guardians*, who reported across England, in disconnected areas. The other two groups contained prolific guardians who covered large areas, with some key clusters of reports, possibly in line with 'nodes', and many reports inbetween these, possibly in line with 'paths'. Overall, like motivated offenders and suitable targets, guardianship also follows spatial patterns, and possibly moves around in place and time, like how opportunity theories have elaborated for the former.

These findings have implications for guardianship research, and the consideration of the role of guardians, and their engagement in crime prevention initiatives. Operationalising guardianship as attributes of the neighbourhood of residence, or neighbourhood of work might be an oversimplification of their behaviour patterns, and should be reconsidered.

Instead, the guardianship offered by these types of guardians might be better captured by micro-level spatially and temporally explicit data about their movement patterns, such as a set of nodes and paths, that can be used to build guardianship templates. Similarly as to how new forms of data from mobile phone signals, or twitter are being used to calculate ambient population of “suitable targets”, data from such civic engagement platforms might better represent the ambient population of such “super and large neighbourhood guardians”.

Finally the neighbourhood agnostic guardians cannot be represented by this neighbourhood-focused approach. These people seem to participate in FMS independent from any connection with the neighbourhood in terms of social cohesion, or collective efficacy, and instead just report in disparate, unconnected places, possibly motivated by the issues they are reporting, rather than some ownership felt over the location. Future research could look into qualitative differences between this group and traditional guardians, and super and large neighbourhood guardians, that might uncover an entirely different motivation to act as guardians than previous theoretical frameworks have proposed. Another topic to explore is whether this group, rather than being “more topic agnostic”, might actually be reporting issues considered more “serious” by some measure. The difference in categories reported in, and any indicators of severity in the descriptions of the reports would be valuable to further dissect.

The groups further differ on other characteristics, such as the number of reports they make, and the diversity of topics in which they report. Evidently guardians cannot be considered a homogeneous group in their spatial behaviour. They exhibit different spatial patterns, and as such have different capacity to act as the capable guardian element of the crime triangle. Like Moir’s typology categorising guardians based on their motivation (Moir, 2016), this grouping allows exploring of guardians’ routine activities outside the home, and reveals a heterogeneity that emphasises the importance of the routine activities and awareness space on influencing where and when guardians are available to intervene.

There are limitations associated with this study, firstly in relation to the data. Crowdsourced data is characterised by bias sample self-selection, as well as participation inequality. Here we made use of this participation inequality to select only the most active guardians, but care should be given to interpreting these results as representative of all guardianship behaviour. This paper considers specifically digitally enabled guardianship, facilitated by civic engagement platforms, such as FMS, which might be qualitatively different from guardianship in person. The assumption that these people represent active guardians is one which could be further explored with qualitative, interview-based research aimed to learn more about the offline behaviour of FMS participants. The demographic makeup of super guardians would be interesting to explore as well. While the crowdsourced data does not include such information, it is possible to complement this with follow-up surveys.

Another possible difference between guardians in the different typologies can be the type of area in which they live. For instance, is it possible that “super neighbourhood guardians” live in high-density urban areas, whereas agnostic guardians are more common in more low-density rural areas? Further research could explore this question in more nuances.

A note on the ethics of such research should be made, accounting for the impact of using digital traces from participation in civic tech on practices related to sharing or concealing information, such as privacy, surveillance, or identification (Elwood, Goodchild, & Sui, 2012). In particular the issue of ‘mining’ data aggregated from individuals who are likely unaware that their information is being gathered or used for research purposes (Vayena, Mastroianni, & Kahn, 2012). Balancing the minimising of risk of harm to individuals with the benefits to the population through research is one approach to making a case for using such data. Consent from data owner should also be sought, and in this case was acquired from MySociety (2016), who run FMS. Finally, care was taken to not make use of personal information (Crawford & Finn, 2015). While these issues must be addressed, there is a case

to be made for the use of crowdsourced data actually being more ethical as opposed to the big and broad data generated by companies, as it can actually provide a more engaged and open data source (Housley et al., 2014) . However it is important to keep open discussion with citizens and researchers on this topic.

Overall this research has implications for development of guardianship theory, and ultimately for crime prevention initiatives that aim to decrease crime risk by motivating capable guardianship. This paper demonstrates making use of data from civic tech participation to gain insight into spatial patterns of individual-level guardianship behaviour, to contribute to the discussion of operationalising guardianship, and people's experiences and perceptions in general, to some measure of neighbourhood. The results indicate that treating guardians as a homogenous group masks variation in their behaviour, both regarding the spatial patterns and their capacity to intervene. Instead, it is possible to make use of civic tech data to explore people's engagement in guardianship and map their guardianship capacity in physical space using digital traces of behaviour available online.

## Bibliography

- Adnan, M., Longley, P. A., Singleton, A. D., & Brunsdon, C. (2010). Towards Real-Time Geodemographics: Clustering Algorithm Performance for Large Multidimensional Spatial Databases. *Transactions in GIS*, 14(3), 283–297. <http://doi.org/10.1111/j.1467-9671.2010.01197.x>
- Anderson, T. K. (2009). Kernel density estimation and K-means clustering to profile road accident hotspots. *Accident Analysis & Prevention*, 41(3), 359-364.
- Anselin, L., & Williams, S. (2016). Digital neighborhoods. *Journal of Urbanism*, 9(4), 305–328. <https://doi.org/10.1080/17549175.2015.1080752>
- Bakolis, I., Hammoud, R., Smythe, M., Gibbons, J., Davidson, N., Tognin, S., & Mechelli, A. (2018). Urban Mind: Using Smartphone Technologies to Investigate the Impact of Nature on Mental Well-Being in Real Time. *BioScience*, 68(2), 134–145. <http://doi.org/10.1093/biosci/bix149>
- Bernasco, W., & Nieuwbeerta, P. (2005). How Do Residential Burglars Select Target Areas? *The British Journal of Criminology*, 45(3), 296–315. <http://doi.org/10.1093/bjc/azh070>
- Bivand, R. (2010). Exploratory Spatial Data Analysis. In M. M. Fischer & A. Getis (Eds.), *Handbook of Applied Spatial Analysis* (pp. 219–254). Berlin, Heidelberg: Springer Berlin Heidelberg. <https://doi.org/10.1007/978-3-642-03647-7>
- Bivand, R., & Rundel, C. (2017). Package “rgeos.” Retrieved February 27, 2018, from <https://cran.rstudio.com/web/packages/rgeos/rgeos.pdf>
- Boehner, K., & DiSalvo, C. (2016). Data, Design and Civics. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems - CHI '16* (pp. 2970–2981). New York, New York, USA: ACM Press. <http://doi.org/10.1145/2858036.2858326>
- Borges, J., Ziehr, D., Beigl, M., Cacho, N., Martins, A., Sudrich, S., ... Popp, J. (2017). Feature Engineering for Crime Hotspot Detection. *IEEE International Conference on*

- Smart City Innovations (IEEE SCI 2017)*, 1–8.
- Brantingham, P., & Brantingham, P. L. (2008). Crime Pattern Theory. In *Environmental Criminology and Crime Analysis* (pp. 78–93). Taylor & Francis.
- Brock, G. (2014). clValid. Retrieved from <https://www.rdocumentation.org/packages/clValid>
- Brunton-Smith, I., Sutherland, A., & Jackson, J. (2013). The Role of Neighbourhoods in Shaping Crime and Perceptions of Crime. In D. Manley, M. van Ham, N. Bailey, L. Simpson, & D. Maclennan (Eds.), *Neighbourhood Effects or Neighbourhood Based Problems? A Policy Context* (pp. 67–87). Dordrecht: Springer Netherlands
- Bursik, R. J. (1988). Social Disorganization And Theories Of Crime And Delinquency: Problems And Prospects. *Criminology*, 26(4), 519–552. <http://doi.org/10.1111/j.1745-9125.1988.tb00854.x>
- Charrad, M., Ghazzali, N., Boiteau, V., & Niknafs, A. (2014). NbClust : An R Package for Determining the Relevant Number of Clusters in a Data Set. *Journal of Statistical Software*, 61(6). <http://doi.org/10.18637/jss.v061.i06>
- Charreire, H., Feuillet, T., Roda, C., Mackenbach, J. D., Compernelle, S., Glonti, K., ... Oppert, J.-M. (2016). Self-defined residential neighbourhoods: size variations and correlates across five European urban regions. *Obesity Reviews*, 17, 9–18
- Cohen, E. L., & Felson, M., (1979). Social Change and Crime Rate Trends : A Routine Activity Approach. *American Sociological Review*, 44(4), 588–608.
- Crawford, K., & Finn, M. (2015). The limits of crisis data: analytical and ethical challenges of using social and mobile data to understand disasters. *GeoJournal*, 80(4), 491–502.
- Curman, A. S., Andresen, M. A., & Brantingham, P. J. (2015). Crime and place: a longitudinal examination of street segment patterns in Vancouver, BC. *Journal of Quantitative Criminology*, 31(1), 127-147.
- Elwood, S., Goodchild, M. F., & Sui, D. Z. (2012). Researching Volunteered Geographic

Information: Spatial Data, Geographic Research, and New Social Practice. *Annals of the Association of American Geographers*, 102(3), 571–590.

Felson, M., Clarke, R. V., & Webb, B. (1998). *Opportunity Makes the Thief: Practical theory for crime prevention. Policing and Reducing Crime Unit: Police Research Series.*

<https://doi.org/10.1186/2193-7680-1-3>

Günter, S., & Bunke, H. (2003). Validation indices for graph clustering. *Pattern Recognition Letters*, 24(8), 1107–1113. [http://doi.org/10.1016/S0167-8655\(02\)00257-X](http://doi.org/10.1016/S0167-8655(02)00257-X)

Gerell, M. (2017). Smallest is Better? The Spatial Distribution of Arson and the Modifiable Areal Unit Problem. *Journal of Quantitative Criminology*, 33(2), 293–318.

Hipp, J. (2010a). Micro-structure in micro-neighborhoods : A new social distance measure , and its effect on individual and aggregated perceptions of crime and disorder. *Social Networks*, 32(2), 148–159.

Hipp, J. (2010b). What is the “neighbourhood” in neighbourhood satisfaction? comparing the effects of structural characteristics measured at the micro-neighbourhood and tract levels. *Urban Studies*, 47(12), 2517–2536.

Hipp, J. R., Bates, C., Lichman, M., & Smyth, P. (2018). Using Social Media to Measure Temporal Ambient Population: Does it Help Explain Local Crime Rates?. *Justice Quarterly*, 1-31.

Hollis-Peel, M. E., Reynald, D. M., van Bavel, M., Elffers, H., & Welsh, B. C. (2011). Guardianship for crime prevention: A critical review of the literature. *Crime, Law and Social Change*, 56(1), 53–70.

Karney, C. F. F. (2013). Algorithms for geodesics. *Journal of Geodesy*, 87(1), 43–55. <http://doi.org/10.1007/s00190-012-0578-z>

Kononenko, I., & Kukar, M. (2007). *Machine learning and data mining: introduction to principles and algorithms*. Elsevier.



- Lee, A. H., McCormick, T., Spiro, E., & Cesare, N. (2015). Exploring the Relationship between Citizens and the Police Via Twitter. *Journal of Quantitative Criminology*, 31(3), 509–535.
- Lupton, R. (2003). “Neighbourhood effects”: can we measure them and does it matter? *CASE Paper 73*, (September), 24. Retrieved from [http://eprints.lse.ac.uk/6327/1/Neighbourhood\\_Effects\\_Can\\_we\\_measure\\_them\\_and\\_does\\_it\\_matter.pdf](http://eprints.lse.ac.uk/6327/1/Neighbourhood_Effects_Can_we_measure_them_and_does_it_matter.pdf)
- Malleson, N., & Andresen, M. a. (2015). The impact of using social media data in crime rate calculations: shifting hot spots and changing spatial patterns. *Cartography and Geographic Information Science*, 42(2), 112–121. <http://doi.org/10.1080/15230406.2014.905756>
- Manley, D., Flowerdew, R., & Steel, D. (2006). Scales, levels and processes: Studying spatial patterns of British census variables. *Computers, Environment and Urban Systems*, 30(2), 143–160.
- Melgaco, L. (2016). The revolution will be more than televised. Retrieved February 26, 2018, from <http://www.enargywebzine.eu/spip.php?article434>
- Moir, E. C. (2016). *Guardianship in the Brisbane Suburbs: An Exploratory Study of Crime Control by Residents in a Non-Urban Context*. Griffith University.
- Moir, E. C., Stewart, A., Reynald, D. M., & Hart, T. C. (2017). Guardianship in Action (GIA) Within Brisbane Suburbs. *Criminal Justice Review*, 42(3), 254–269. <http://doi.org/10.1177/0734016817724199>
- Moro, S., Cortez, P., & Rita, P. (2014). A data-driven approach to predict the success of bank telemarketing. *Decision Support Systems*, 62, 22–31. <http://doi.org/10.1016/j.dss.2014.03.001>
- MySociety. (2016). MySociety About page. Retrieved from

<https://www.mysociety.org/about/>

- Newton, A. D., & Bowers, K. J. (2007). The geography of bus shelter damage: The influence of crime, neighbourhood characteristics and land-use. *Internet Journal of Criminology*. Retrieved from <http://eprints.hud.ac.uk/id/eprint/474/1/NewtonGeography.pdf>
- O'Brien, D. T., Sampson, R. J., & Winship, C. (2015). Econometrics in the Age of Big Data. *Sociological Methodology*, 45(1), 101–147. <http://doi.org/10.1177/0081175015576601>
- O'Connor, S. (2010). *Maps for Advocacy: An Introduction to Geographical Mapping Techniques*. India: Tactical Technology Collective. Retrieved from <http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:Maps+for+Advocay:+an+Introduction+to+Geographical+Mapping+Techniques#2>
- Office for National Statistics. (2017). Census geography. Retrieved February 27, 2018, from <https://www.ons.gov.uk/methodology/geography/ukgeographies/censusgeography/143-160>. <https://doi.org/10.1016/j.compenvurbsys.2005.08.005>
- Openshaw, S. (1984). Ecological Fallacies and the Analysis of Areal Census Data. *Environment and Planning A*, 16(1), 17–31.
- Raykov, Y. P., Boukouvalas, A., Baig, F., & Little, M. A. (2016). What to Do When K-Means Clustering Fails: A Simple yet Principled Alternative Algorithm. *PLOS ONE*, 11(9), e0162259. <http://doi.org/10.1371/journal.pone.0162259>
- Rengert, G. F., & Lockwood, B. (2009). Geographical Units of Analysis and the Analysis of Crime. In D. Weisburd, W. Bernasco, & G. J. N. Bruinsma (Eds.), *Putting Crime in its Place* (pp. 109–122). New York, NY: Springer New York.
- Reynald, D. M. (2009). Guardianship in action: Developing a new tool for measurement. *Crime Prevention and Community Safety: An International Journal*, 11(1), 1–20. <http://doi.org/10.1057/cpcs.2008.19>
- Reynald, D. M. (2011). *Guarding against crime: Measuring guardianship within routine*

*activity theory*. Ashgate Publishing, Ltd.

- Rumbul, R. (2015). *Who Benefits From Civic Technology?* Online. Accessed: 27 February 2018. Retrieved from <http://research.mysociety.org/publications/who-benefits-from-civic-technology>
- Sarstedt, M., & Mooi, E. (2014). Cluster Analysis (pp. 273–324). [http://doi.org/10.1007/978-3-642-53965-7\\_9](http://doi.org/10.1007/978-3-642-53965-7_9)
- Şenbabaoğlu, Y., Michailidis, G., & Li, J. Z. (2015). Critical limitations of consensus clustering in class discovery. *Scientific Reports*, 4(1), 6207. <http://doi.org/10.1038/srep06207>
- Sengupta, A. (2009). *Advances in Multivariate Statistical Methods*. (S. K. Pal, Ed.) (Statistica). Singapore: World Scientific.
- Shiramatsu, S., Tossavainen, T., Ozono, T., & Shintani, T. (2015). Towards Continuous Collaboration on Civic Tech Projects: Use Cases of a Goal Sharing System Based on Linked Open Data (pp. 81–92). [http://doi.org/10.1007/978-3-319-22500-5\\_7](http://doi.org/10.1007/978-3-319-22500-5_7)
- Solymosi, R., Bowers, K., & Fujiyama, T. (2015). Mapping fear of crime as a context-dependent everyday experience that varies in space and time. *Legal and Criminological Psychology*, 20(2).
- Solymosi, R., Bowers, K. J., & Fujiyama, T. (2017). Crowdsourcing Subjective Perceptions of Neighbourhood Disorder: Interpreting Bias in Open Data. *The British Journal of Criminology*, 58(4), 944-967.
- Solymosi, R., & Bowers, K. (2018). The role of innovative data collection methods in advancing criminological understanding. *The Oxford Handbook of Environmental Criminology*, 210.
- Stewart, O., Lubensky, D., & Huerta, J. M. (2010). Crowdsourcing participation inequality: a SCOUT model for the enterprise domain. In *Proceedings of the ACM SIGKDD*

*Workshop on Human Computation* (pp. 30–33).

- Sturgis, P., Brunton-Smith, I., Kuha, J., & Jackson, J. (2014). Ethnic diversity, segregation and the social cohesion of neighbourhoods in London. *Ethnic and Racial Studies*, 37(8), 1286–1309.
- Trevino, A. (2016). Introduction to K-means Clustering. Retrieved February 27, 2018, from <https://www.datascience.com/blog/k-means-clustering>
- Vayena, E., Mastroianni, A., & Kahn, J. (2012). Ethical issues in health research with novel online sources. *American Journal of Public Health*, 102(12), 2225–2230.
- Weisburd, D., Bruinsma, G., & Bernasco, W. (2009). Units of analysis in geographic criminology: Historical development, critical issues, and open questions. *Putting Crime in Its Place: Units of Analysis in Geographic Criminology*, 3–31.  
[https://doi.org/10.1007/978-0-387-09688-9\\_1](https://doi.org/10.1007/978-0-387-09688-9_1)
- Weisburd, D., Groff, E. R., & Yang, S. M. (2012). *The criminology of place: Street segments and our understanding of the crime problem*. Oxford University Press.
- Wikstrom, P.-O. H., Ceccato, V., Hardie, B., & Treiber, K. (2010). Activity Fields and the Dynamics of Crime : Advancing Knowledge About the Role of the Environment in Crime Causation. *Journal of Quantitative Criminology*, 26(1), 55-87
- Williams, M. L., Burnap, P., & Sloan, L. (2016). Crime Sensing with Big Data: The Affordances and Limitations of using Open Source Communications to Estimate Crime Patterns. *British Journal of Criminology*, azw031. <http://doi.org/10.1093/bjc/azw031>
- Wood, D. (2010). *Rethinking the Power of Maps*. London: The Guildford Press.
- Woodruff, A. (2012). Crowdsourced neighbourhood boundaries, Part One: Consensus. Retrieved July 25, 2018, from <http://bostonography.com/2012/crowdsourced-neighborhood-boundaries-part-one-consensus>

