Article

Criminal Justice Review
1-18

Article reuse guidelines:
sagepub.com/journals-permissions
DOI: 10.1177/0734016818813428
journals.sagepub.com/home/cjr
SAGE

# Exploring Spatial Patterns of Guardianship Through Civic Technology Platforms

**Reka Solymosi**[1]

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

**Keywords**
guardianship, civil tech, crowdsourcing, spatial patterns, neighborhood

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 toward 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 toward 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

[1] School of Law, University of Manchester, Manchester, United Kingdom

**Corresponding Author:**
Reka Solymosi, School of Law, University of Manchester, Room 4.53 Williamson Building, Oxford Road, Manchester M13 9PL, United Kingdom.
Email: reka.solymosi@manchester.ac.uk

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 article 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 operationalizing guardianship in public places as an attribute of neighborhoods. 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 behavior relates to traditional approaches to analysis of guardianship.

The contribution of this article therefore is 2-fold. First, exploratory spatial data analysis is used to map individual-level spatial patterns in guardianship behavior, with reference to some measure of neighborhood. Second, based on the spatial patterns of guardianship behavior, 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 neighborhoods and that guardians, even active guardians, should not be treated as one homogeneous group.

## Theoretical Background

### Civic Engagement and the Democratization 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 (Malleson & 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 democratize 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 democratization 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 "countermap," 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 neighborhood 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 neighborhood 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 creates a catalog of issues reported. Such data have been used to represent the 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 neighborhood, this participation also shows where the people reporting go and actively monitor their environments. The innovation of this article 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 behavior 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 behavior while in the home.

However, measurement of guardianship in public spaces has not yet incorporated this theoretical innovation of guardianship in action into its operationalization. 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 conceptualizing 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 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 neighborhood (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' behavior 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 neighborhood (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 behavior 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 behavior 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 behavior. 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 conceptualize guardianship from a crime pattern perspective, rather than focus on it as a feature associated with a spatial unit such as a neighborhood, which itself brings about a series of conceptual challenges.

## *The Neighborhood as a Unit of Analysis*

As mentioned above, guardianship is often measured at an aggregate spatial unit of analysis, such as neighborhood. The theoretical framework of social disorganization theory, for example, postulates a link between neighborhood disorganization and guardianship (Bursik, 1988). Guardianship in this instance is operationalized 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 neighborhood. The issue of operationalizing neighborhood 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 neighborhoods (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 neighborhood satisfaction covariates were measured at local micro-neighborhood 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 "neighborhood" (Hipp, 2010b).

But a particular challenge for the study of people's activity patterns is to define the limits of neighborhood, 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 neighborhood 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 redrawing of neighborhood boundaries (Woodruff, 2012), or to use social media data to identify "digital neighborhoods" (Anselin & Williams, 2016). These approaches share a reach for new forms of data to aid the reframing of the concept of neighborhood. 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 article addresses the following hypotheses: The awareness space of guardians, and therefore area where they act as guardians through reporting neighborhood issues, is not limited to neighborhood as defined by administrative boundaries.

Spatial patterns of guardianship behavior 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 come 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 characterized 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 article is to consider the movement of active guardians. To ensure the measure reflects this, active guardians were operationalized 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 were 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%, nonpeople names which could have been associated with multiple people were removed (e.g., "customer service center" 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 are also used to answer the questions about the suitability of aggregating guardianship behavior to neighborhoods. Earlier, the issue with attributing guardianship as a parameter of a neighborhood was discussed. Lower layer super output area (LSOA) is a commonly used geography to represent neighborhoods 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 neighborhood data are used to create a new variable for the number of neighborhoods guardians report in, as well as used for the feature engineering part of the analysis.

## Method

The article will first consider a descriptive analysis of people's reporting behavior through exploratory spatial data analysis (ESDA; Bivand, 2010), to annotate guardianship behavior 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 are 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' behaviors through clustering analysis.

Finally, cluster analysis is used to create typologies of guardians' behaviors. 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 hot spot 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 article 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 intracluster 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 Behavior 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 behavior 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 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 behavior.

While heterogeneity of topics people report, and in volume of reporting offers insight into guardianship behavior, to answer the questions about the spatial patterns, the number of neighborhoods in which people report is considered. There were only six people who reported in only one neighborhood, fewer than the number of people who reported in only one category. The other 409 contributors all reported in at least two neighborhoods. Interestingly, the top reporter (person with highest number of reports) was not the person who reported in the highest number of neighborhoods. The average number of neighborhoods in which people reported was 17 neighborhoods (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 that does not line up with an administrative boundary definition of neighborhood. Guardians captured by this measure report in many neighborhoods and assigning them as guardians over only the one neighborhood that 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 behavior.

Besides descriptive statistics, ESDA comprises of visualizations 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 characterized by high connectivity between LSOAs where neighborhoods 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.

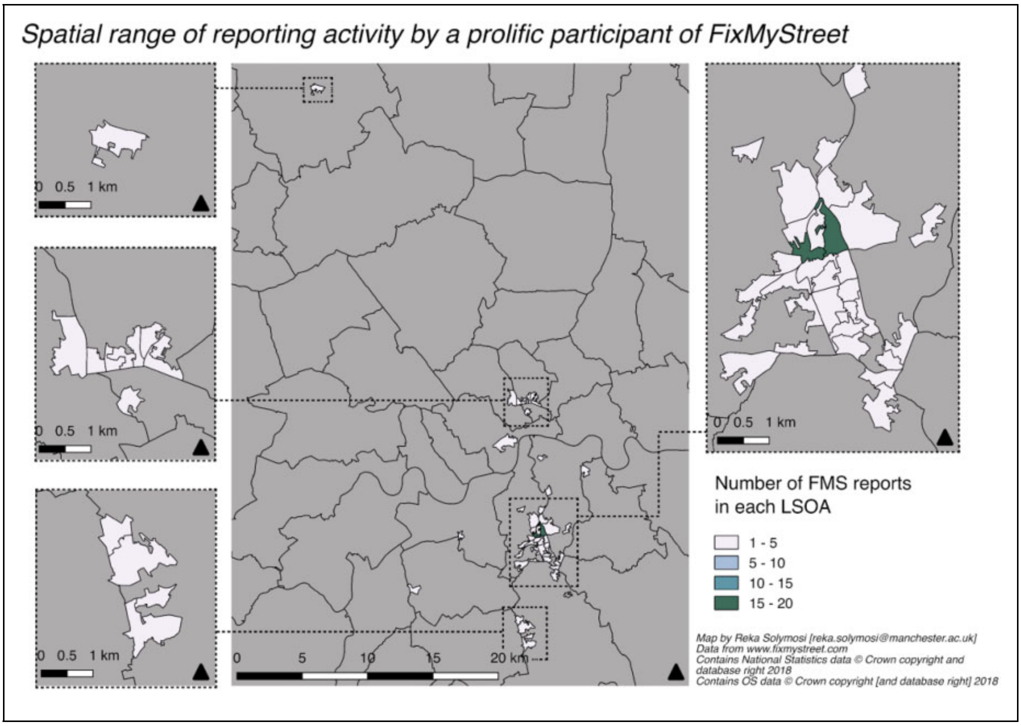


**Figure 1.** Participant with many far away neighborhoods.

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

It is evident that differences in spatial patterns of behavior 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 toward heterogeneity in guardianship activity and in particular in the spatial patterns of issue reporting. It revealed that guardians are not only active within their neighborhoods, and instead their spatial patterns resemble activity nodes connected by paths, highlighting an awareness space characterized 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 behavior:

- Number of neighborhoods (LSOAs): According to traditional approaches to conceptualizing and operationalizing guardianship at neighborhood 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 neighborhoods 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 neighborhoods 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 neighborhoods, and how connected they are, it can make a difference how far apart these neighborhoods 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 behavior, 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 behavior patterns: their range (number of neighborhoods they guard), compactness (connectivity of the neighborhoods they guard), and reach (distance between neighborhoods they guard). All the results were standardized 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 behavior 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 "neighbor" 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 rerunning the analysis with $k = 3$, and $k = 5$ further confirms that $k = 4$ is a reasonable number of clusters. Rerunning 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 behavior 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 behavior. The next section will explore these clusters.

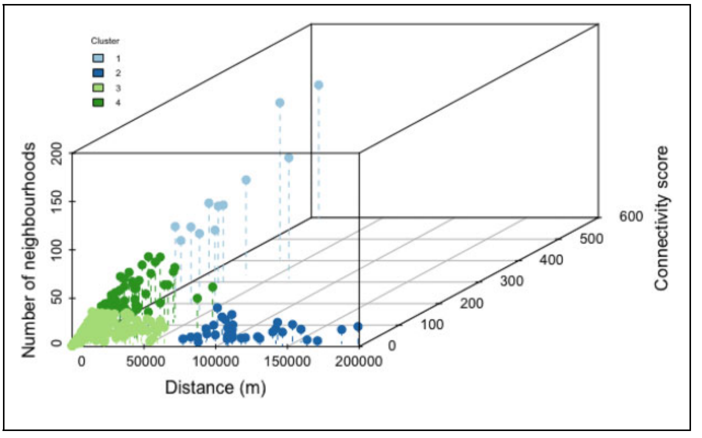


**Figure 2.** 3-D scatterplot of features.

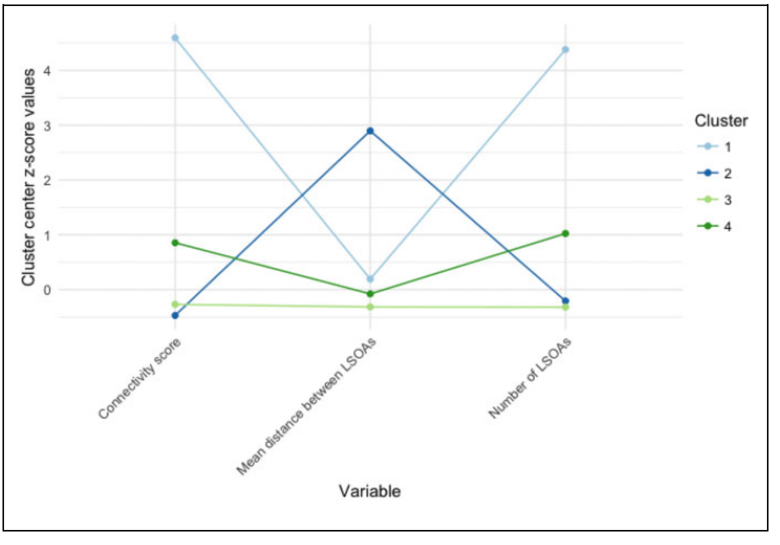


**Figure 3.** Cluster values for features.

## *Guardianship Typologies*

Figures 2 and 3 help visualize 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.

*Cluster* 1 represents people who report in a high number of neighborhoods 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 neighborhoods. The high connectivity score means that these neighborhoods are clustered together, and this is reaffirmed by the low average distance between neighborhoods (around 26 km). This group represents *super neighborhood guardians* who act as active guardians across the range of their activity space, which covers a large number of neighborhoods defined by LSOAs.

*Cluster* 2 is the opposite of Cluster 1. These guardians report in a low number of neighborhoods (average of 13) that are not highly connected (lowest score of all clusters) and are far away from one

**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 | 26,224 | 19,501 | 2,442 | 29,018 | 63,238 |  |
| | 2 | 11,7986 | 30,132 | 77,212 | 10,8713 | 19,6970 |  |
| | 3 | 9,025 | 12,696 | 0 | 3,682 | 60,295 |  |
| | 4 | 17,096 | 17,071 | 1,437 | 11,665 | 78,428 |  |
| 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 |  |

*Note*. LSOA = layer super output area.

another. The mean distance between the neighborhoods is 118 km, by far the largest for all clusters. This means that these people anywhere they go, when they encounter something they report it. They are *neighborhood agnostic guardians* who report any issue they come across, anywhere in their activity space.

*Cluster* 3 have the highest number of people, representing the modal behavior of FMS participants. This most common spatial pattern is characterized by consistently low number of neighborhoods (mean of 11), with relatively low connectivity compared to other groups (higher only than cluster two), but not too far apart (mean distance of 9 km). These are the *traditional guardians* who focus on their areas of familiarity, which is a smaller activity space than other clusters.

Finally, *Cluster* 4 shows patterns similar to cluster one, with high number of neighborhoods (mean of 34), highly connected, and further apart from one another, but report in not as many neighborhoods nor as far apart as the super neighborhood guardians. This behavior can be understood as a less "extreme" version of cluster one. For example, the average number of neighborhoods in which members of this cluster report are 35, which is significantly higher than Clusters 2 and 3, but just over a third of the number of neighborhoods 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 neighborhood guardians*, as their spatial range is larger than the *traditional guardian* (cluster three) and smaller than the *super neighborhood guardian* (cluster one) but is characterized by higher connectivity than the *neighborhood 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.

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 neighborhood guardians are the most prolific reporters, followed by large neighborhood guardians, whereas the neighborhood agnostic guardians are least prolific, reporting only when they encounter something that motivates them to report. Indeed, analysis of variance (ANOVA) results show support for this hypothesis ($p < .001$, $F = 27.29$, $df = 1$). 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.

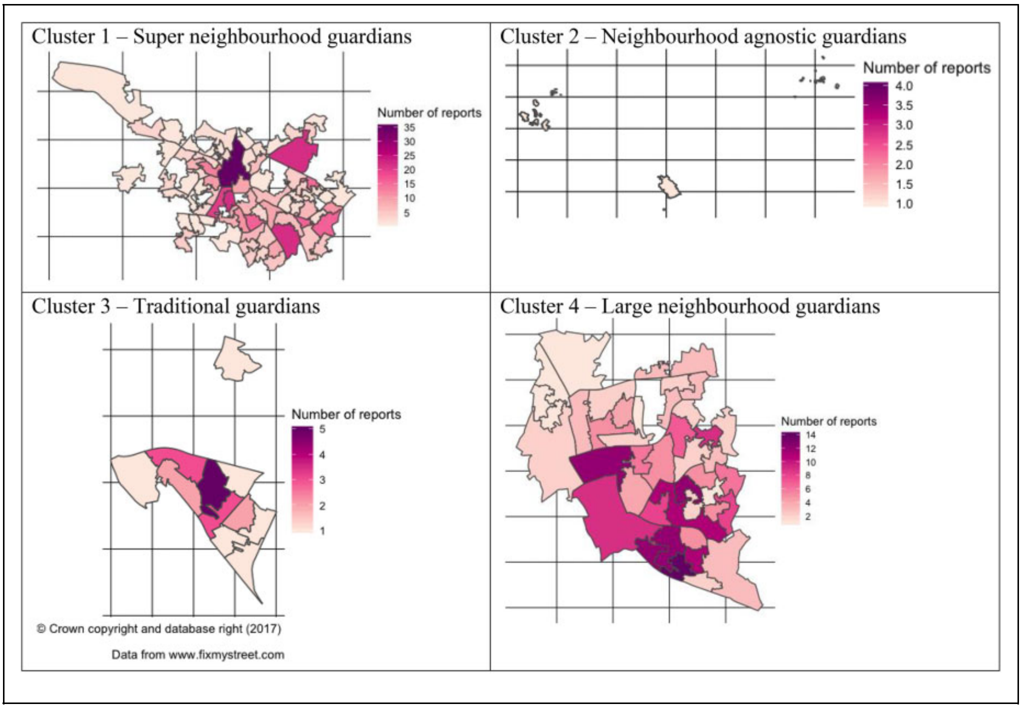


**Figure 4.** Example maps for each cluster.

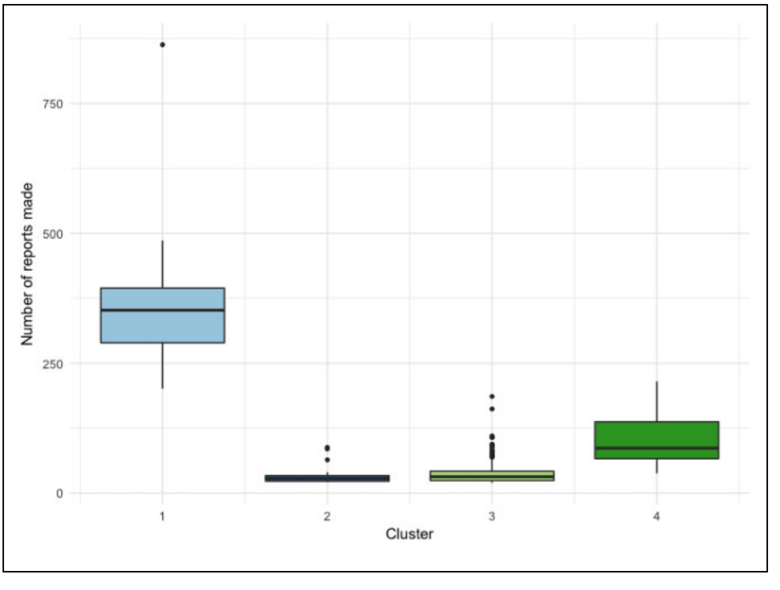


**Figure 5.** Number of FMS reports by cluster.

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 neighborhood 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 *neighborhood agnostic guardians* (Cluster 2). It seems that not only are these people neighborhood 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 ($p = .124$, $F = 2.372$, $df = 1$), so a difference between the diversity of topics in which these guardians report cannot be supported. However, to test the assumption that the neighborhood 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 neighborhood agnostic group report, compared to the traditional guardianship group ($t = 2.8$, $df = 42.3$, $p$ value $= .008$, Cohen's $d$ estimate $= -.5$ [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 neighborhood 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 neighborhood is a meaningful way to operationalize guardianship. Issues with defining neighborhoods were discussed, with particular focus on the discrepancy between administrative geographies and people's subjective definitions of neighborhood. In this instance, if a commonly used operationalization of neighborhood (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 behavior was evaluated using clustering. Results grouped guardianship behavior 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, labeled *traditional guardians*, can be considered to fit into the framing of a guardian of their neighborhood. While their idea of a neighborhood definitely does not correspond with administrative boundaries (they cover on average 9 LSOAs), it is possible that by reframing the concept of neighborhood 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 neighborhood in line with social disorganization theories that emphasize 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 neighborhood but also throughout their activity space. This was observed with the *neighborhood 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 in-between 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. Operationalizing guardianship as attributes of the neighborhood of residence, or neighborhood of work might be an oversimplification of their behavior 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 neighborhood guardians."

Finally, the neighborhood agnostic guardians cannot be represented by this neighborhood-focused approach. These people seem to participate in FMS independent from any connection with the neighborhood 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 neighborhood 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 behavior. 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 (2016) typology categorizing guardians based on their motivation, this grouping allows exploring of guardians' routine activities outside the home and reveals a heterogeneity that emphasizes 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 are characterized 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 case should be given to interpreting these results as representative of all guardianship behavior. This article 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 off-line behavior of FMS participants. The demographic makeup of super guardians would be interesting to explore as well. While the crowdsourced data do 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 neighborhood 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 minimizing 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 the development of guardianship theory and ultimately for crime prevention initiatives that aim to decrease crime risk by motivating capable guardianship. This article demonstrates making use of data from civic tech participation to gain insight into spatial patterns of individual-level guardianship behavior, to contribute to the discussion of operationalizing guardianship, and people's experiences and perceptions in general, to some measure of neighborhood. The results indicate that treating guardians as a homogenous group masks variation in their behavior, 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 behavior available online.

## Author's Note

This work is original and has not been published elsewhere.

## Acknowledgments

The author would like to thank Emily Turner and Professor Vania Ceccato, as well as the two anonymous reviewers for their comments on earlier drafts of this paper.

## Declaration of Conflicting Interests

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

## Funding

The author received no financial support for the research, authorship, and/or publication of this article.

## References

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*, 283–297. doi: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*, 359–364.

Anselin, L., & Williams, S. (2016). Digital neighborhoods. *Journal of Urbanism*, *9*, 305–328. doi: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*, 134–145. doi:10.1093/biosci/bix149

Bernasco, W., & Nieuwbeerta, P. (2005). How do residential burglars select target areas? *The British Journal of Criminology*, *45*, 296–315. doi: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, Germany: Springer. doi: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, NY: ACM Press. doi: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). Didcot, England: Taylor & Francis.

Brantingham, P. L., & Brantingham, P. J. (1993). Nodes, paths and edges: Considerations on the complexity of crime and the physical environment. *Journal of Environmental Psychology*, *13*, 3–28.

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, the Netherlands: Springer.

Bursik, R. J. (1988). Social disorganization and theories of crime and delinquency: Problems and prospects. *Criminology*, *26*, 519–552. doi: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*, 1–36. doi:10.18637/jss.v061.i06

Charreire, H., Feuillet, T., Roda, C., Mackenbach, J. D., Compernolle, 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*, 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*, 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*, 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*, 571–590.

Felson, M., Clarke, R. V., & Webb, B. (1998). *Opportunity makes the thief: Practical theory for crime prevention*. London, England: Policing and Reducing Crime Unit: Police Research Series. doi:10.1186/2193-7680-1-3

Gerell, M. (2017). Smallest is better? The spatial distribution of arson and the modifiable areal unit problem. *Journal of Quantitative Criminology*, *33*, 293–318.

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

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*, 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*, 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*, 53–70.

Housley, W., Procter, R., Edwards, A., Burnap, P., Williams, M., Sloan, L., & Greenhill, A. (2014). Big and broad social data and the sociological imagination: A collaborative response. *Big Data & Society*, *1*, 1–15. doi:10.1177/2053951714545135

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

Kononenko, I., & Kukar, M. (2007). *Machine learning and data mining: introduction to principles and algorithms*. Amsterdam, the Netherlands: 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*, 509–535.

Lupton, R. (2003, September 24). “Neighbourhood effects”: Can we measure them and does it matter? *CASE Paper 73*, 24. Retrieved from 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*, 112–121. doi: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*, 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*. Brisbane, Australia: 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*, 254–269. doi: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. doi: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). Ecometrics in the age of big data. *Sociological Methodology*, *45*, 101–147. doi: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. doi:10.1016/j.compenvurbsys.2005.08.005

Openshaw, S. (1984). Ecological fallacies and the analysis of areal census data. *Environment and Planning A*, *16*, 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*, e0162259. doi: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.

Reynald, D. M. (2009). Guardianship in action: Developing a new tool for measurement. *Crime Prevention and Community Safety: An International Journal*, *11*, 1–20. doi:10.1057/cpcs.2008.19

Reynald, D. M. (2011). *Guarding against crime: Measuring guardianship within routine activity theory*. Farnham, England: Ashgate.

Rumbul, R. (2015). *Who benefits from civic technology?* Retrieved February 27, 2018, from http://research.mysociety.org/publications/who-benefits-from-civic-technology

Sarstedt, M., & Mooi, E. (2014). *Cluster analysis* (pp. 273–324). doi: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*, 6207. doi:10.1038/srep06207

Sengupta, A. (2009). Advances in multivariate statistical methods. In 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. In: E. Tambouris, et al. (Eds.), *Electronic Participation* (pp. 81–92). Cham: Springer.

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*, 193–211.

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*, 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*, 210–237.

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*, 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*, 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. doi:10.1007/978-0-387-09688-9_1

Weisburd, D., Groff, E. R., & Yang, S. M. (2014). *The criminology of place: Street segments and our understanding of the crime problem*. Oxford, England: 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*, 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. doi:10.1093/bjc/azw031

Wood, D. (2010). *Rethinking the power of maps*. London, England: 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

## Author Biography

**Reka Solymosi** is a lecturer in Quantiative Methods at the Centre for Criminology and Criminal Justice in School of Law, University of Manchester. Her research interests are in data analysis and visualisation, crowdsourcing, rstats, fear of crime, public transport, and collecting data about everyday life. She is particularly interested in new forms of data and new approaches to measuring perception of crime and place.