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Mapping Connections between Neighborhoods in Response to Community-Based Social Needs

Carmelina Bevilacqua [1,*], Poya Sohrabi [2], Nourhan Hamdy [2] and Federica Mangiulli [2]

[1] Pianificazione, Design Tecnologia Dell'Architettura (PDTA) Department, La Sapienza University of Rome, Via Flaminia 72, 00196 Roma, Italy

[2] Community Local Urban Development Laboratory (CLUDsLab), Patrimonio, Architettura, Urbanistica (PAU) Department, Università Degli Studi Mediterranea of Reggio Calabria, Via Dell'Università 25, 89124 Reggio Calabria, Italy; poya.sohrabi@unirc.it (P.S.); nourhan.hamdy@unirc.it (N.H.); federica.mangiulli@unirc.it (F.M.)

* Correspondence: carmelina.bevilacqua@uniroma1.it

Abstract: Geographic proximity might not be the only factor influencing the connections between neighborhoods within the same city. Most likely, the community's needs and behaviors play a role in facilitating or hindering any connections between these urban areas. Accordingly, relationships between communities may differ or be similar based on their respective characteristics. This paper aims to demonstrate that communities are close based on the needs they share, regardless of their ethnicity or geographic location. In this study, a time series analysis of neighborhoods' needs is explored to gain a deeper understanding of the communities' network. The study takes into account the co-occurrence of complaints/reports from residents regarding the same issue. The dataset was retrieved from the Boston Area Research Initiative (BARI) and the 311 system that describe the features of neighborhoods regarding non-emergency issues. Subsequently, the connection between neighborhoods in the City of Boston was analyzed using a mixture of PCA, K-means, association rule mining, and a network creation tool. Moreover, clustering coefficients and degrees of centrality were used as significant factors in identifying the members of groups and marking crucial nodes in the network. A series of graphs were generated to show how the neighborhoods are linked based on their socioeconomic concerns. The results prove that even geographically disconnected neighborhoods within Boston have similar social needs, despite their distance from one another. Furthermore, it revealed that some neighborhoods can act as linking bridges for other neighborhoods, while others may be isolated within the network graph. This study has increased awareness of urban aspects. The authorities may consider other dimensions than the traditional ones regarding neighborhood development and addressing problems. Finally, it helps to identify common characteristics between neighborhoods, which facilitates the policy making process.

Keywords: neighborhood connections; cluster analysis; participation; community behavior; social needs; Boston 311; proximity

Citation: Bevilacqua, C.; Sohrabi, P.; Hamdy, N.; Mangiulli, F. Mapping Connections between Neighborhoods in Response to Community-Based Social Needs. *Sustainability* **2023**, *15*, 4898. https://doi.org/10.3390/su15064898

Academic Editor: Miguel Amado

Received: 27 January 2023
Revised: 5 March 2023
Accepted: 6 March 2023
Published: 9 March 2023

1. Introduction

In the same city, there are diverse socioeconomic characteristics among neighborhoods that may influence residents' needs [1,2]. Shared needs can enhance the sense of proximity between residents and help them to become recognized as a community [3,4]. It is arguable that geographical proximity is not the only factor influencing the connections between neighborhoods within the same city. Neighborhoods are places where people live or work near each other. Neighbors are residents who share the same spatial geographical area, but also include shop owners and their employees. In other words, people who frequently visit the neighborhood [5,6]. It is possible to build the connections between different neighborhoods due to human activities and commutes between them, even though they are not directly adjacent to each other. On the one hand, the affective attachment of residents to a neighborhood may vary based on the amount of time that neighbors spend in the area, the local facility usage, and/or its demographic patterns (e.g., the number of children, non-working adults, and elderly people who live in the community). On the other hand, the intensity of the connection between neighborhoods could also depend on the sharing of the same social needs. For example, community behavior is influenced by several factors, including, but not limited to, socioeconomic status, social networks, education, ethnicity, working conditions, physical environment, and health [7]. Therefore, taking into account the diverse characteristics of different neighborhoods would ensure that policies are tailored to the unique needs of the local residents in each neighborhood.

A key element to a better understanding of citizens' needs is encouraging them to share these needs. This will help to strengthen the relationship between institutions and communities, which involves the possibility for citizens to contribute to the decision making process and planning activity. Recent years have seen a resurgence in the interest in involving society in the coproduction or the planning and implementation of government development programs [8,9]. Already, cities like Boston have built service centers and mobile applications that allow for residents to report problems and then track the status of these problems [10]. For example, the 311 system in the US is designed to create "the human touch of small-town life in the context of a vast metropolis" [11]. The 311 service was created to transfer and receive the non-emergency calls coming into 911 systems. Nevertheless, the "311 is now used for performance measurement, economic development and community engagement" [10]. The system has grown to not only respond to complaints but to tackle urban problems before they get bigger.

Despite the availability of the vast literature on community attachment and satisfaction, and their associations with community participation [12,13], the linkage between these factors in different neighborhoods has not yet been clearly investigated [14]. One of the objectives of this study is to introduce a new way of mapping the connections between neighborhoods within the same city based on their common needs. In this regard, the research question is as follows: is there a correlation between community needs in different neighborhoods in the same city? Additionally, if so, to what extent? To answer these questions, the connection between the neighborhoods in the City of Boston was examined based on their behavior and perceptions. To do this, multivariate statistical techniques were used to identify the socioeconomic and demographic characteristics of the neighborhoods in the City of Boston and to classify these neighborhoods based on their similarities of these characteristics.

The paper is structured as follows. In the first part, the theoretical background provides an understanding of the current debate about neighborhood proximity in terms of community needs. This allows the authors to understand the other factors that connect neighborhoods apart from their geographical location. Secondly, a dataset from the Boston Area Research Initiative (BARI) and the 311 system is used to investigate the connection between the neighborhoods in the City of Boston (see Figure 1). Finally, the discussion about the different factors that connect these neighborhoods aims to facilitate the policy making process.

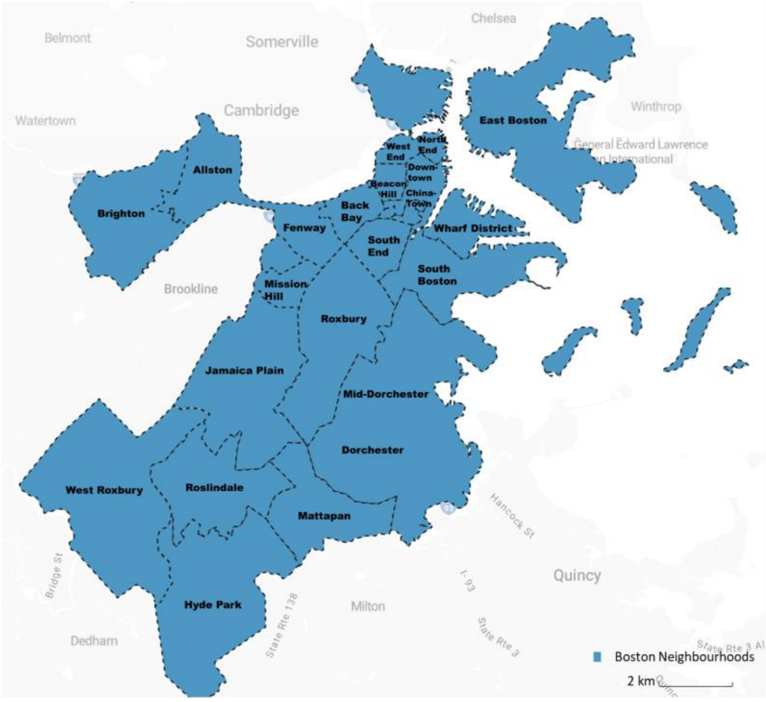

Figure 1. Map of Boston's neighborhoods. Authors' elaboration based on neighborhood maps from The Boston Planning & Development Agency (BPDA).

1.1. City like a Network of Neighborhoods: Applying the Concept of Proximity Based on Communities' Needs

During the last decade, the city networks concept was introduced into regional science, particularly within regional and urban geography [15,16]. It is a geographical concept that describes the interconnectivity of the urban structure [15,17]. City networks could be useful for understanding the spatial phenomena that cannot be analyzed by the usual tools—spatial interaction, urban hierarchy, and social capital—that facilitate urban policies [15]. These networks are generated from the interactions and the exchanges of goods, services, information, and contacts among places and people [15,18].

In the city, everything is interconnected and related to each other, and the main goal of this study is to focus on building a neighborhood network to show a wide range of social realities, and consequently, community needs. Neighborhoods have developed and are defined through historical processes and continue to be influenced by circumstances, individual behavior, and the activities of businesses, governments, social services, and development agencies, and other corporate actors [19]. Despite the administrative structure that characterizes each city that is organized by well-bordered neighborhoods, their definition in terms of the area where people live and engage in activities [20], or residents' proximity to public transport and to work, as well as their walking distances to a range of services [7,21], is challenging, because they could be described based on different features [19]. Other factors, however, should also be considered when connecting neighborhoods. For example, social aspects should be one of the factors that has to be taken into consideration [22].

It is claimed by the authors that the proximity or the closeness between different neighborhoods can be described if two or more neighborhoods share the same social needs. As long as the same event occurs in different places at the same time, then this probably means that the two communities have similar needs and problems to deal with. The proposed method allows for the mutual interactions taking place to be shown, irrespective of geographic proximity. Thinking of a city in these terms can be an innovative way of addressing the urban problem. In fact, identifying the problem's typology, place, time, and frequency can allow us to use the same solution for different places.

1.2. Community Participation Is a Tool to Better Understand Each Community's Needs

In recent years, the debate on urban development shows that traditional planning methods are inadequate for tackling the ongoing problems, challenges, and opportunities that are facing our cities and regions [23]. In this respect, one of the key challenges for planning is to be able to critically assess what type of planning is most appropriate as a way to deal—in an innovative/emancipatory and transformative way—with the problems and challenges that are facing societies [24]. Problem solving needs causal mechanisms like collective action, which could be differentially implemented depending on the context [25].

Citizens' participation in community development, whether by participating in local community institutions and organizations, or by reporting the problems in their neighborhoods, is increasingly being considered to be vital for effective urban service delivery [26]. It is a way to share problems with authorities and is a vital part of any community development process [27]. Throughout history, it has been an important method for improving the quality of the physical environment, enhancing the urban services, and solving problems in many fields such as health and crime [7].

Civic participation stems from a sense of responsibility towards solving neighborhood problems or improving its services for the whole community [28]. If the residents have a sense of community, that can have a catalytic effect on local action. Participation in solving community problems happens based on various factors, such as the residents' feelings about their locality when they know that their reports will be addressed by the authorities [13,29]. Hence, community satisfaction is treated as a key variable that influences community participation [30,31]. Acknowledging residents and stimulating collective action between these residents and the authorities appears to have a significant impact on citizens' sense of identity and community [21]. Therefore, it is important to understand which factors motivate residents' participation [32]. Scholars have claimed that participation is conditioned by culture, politics, and social structure [27]. The different levels of attachment that residents have to their community are factors for the differences in community participation [33–35]. It is important to understand why individuals choose to participate or not in a given program when implementing community-based programs. In fact, programs that involve the public are unlikely to be effective without public participation.

Chavis and Wandersman claimed that there are three components that influence an individual's voluntary participation in neighborhood development [7]. Those components are "the perception of the environment, one's social relations, and one's perceived control and empowerment within the community". Nevertheless, citizens' networks and their sense of community may differ between different types of groups. Moreover, urban researchers have noted the relationship between the overall well-being of a neighborhood and their participation in developing their neighborhood (e.g., [36]). Neighborhoods with higher well-being typically have elevated social participation outcomes.

Other studies that have emphasized individual-level socioeconomic variables identified gender, age, education, income, religious affiliation, and length of residence as the factors influencing community participation [14,37,38]. For example, societies that have a higher percentage of women, married couples, and people with higher incomes and education tend to have broader, dispersed, and more casual neighborhood networks. However, those communities that are less integrated, such as ones with singles, children, elderly people, and more lower income and less educated people, are more likely to have smaller, more engaged relationships within the neighborhood. Therefore, understanding the context of the neighborhood will allow for us to interpret the different aspects of it.

Multiple motivations for coproduction were first recognized by Alford [39]. He identified three types of nonmaterial rewards that might increase one's willingness to participate: intrinsic rewards, such as increased self-esteem as a result of effective action;

solidary incentives, resulting from a desire to contribute to the group; and expressions of values, such as normative beliefs.

Moreover, the physical environment may play a role in local sentiments, such as attachment to the place. It was argued that deprived neighborhoods were less satisfied with their neighborhoods and had a lower emotional response to their neighborhoods. The difference in neighborhood quality, including perceived safety, noise, and place attachment, may still lead to lower levels of neighborhood satisfaction and low emotional responses to neighborhoods, even when green space, public transportation, and local amenities are evenly distributed [38]. Earlier theorists such as Jacobs argued that residents' sense of public responsibility was essential to maintaining a neighborhood. The notion that the residents of a particular neighborhood are concerned about managing or personalizing the appearance of their neighborhood is rooted in their capacity for territoriality [36]. The resident identifies with the local space and feels a sense of attachment to it.

Community participation can enhance the efficiency and effectiveness of services. However, this is only true if the efforts of these two entities are complementary and not interchangeable [40]. Great transparency will help in boosting citizen engagement and empowerment within the city they live in [10]. For example, in a 311 system, the government and the public are responsible for maintaining the urban commons. People who live in cities can observe and report instances of the deterioration and denigration of public spaces, and city agencies can provide the professional expertise and equipment to fix them. It is an example of a highly involved system, since 311 services are not automatic but must be requested through the general reporting of problems.

To sum up, through sharing their needs with authorities, residents are able to direct and shape the development of their neighborhoods. As an example, complaints about graffiti and illegal dumping are among the examples that indicate that citizens are seeking to redirect any degrowth they see in their communities [41]. When community members are active, responsible, and have opportunities to speak, they are more likely to foster their civic engagement in that community. Increasing the opportunities for local interactions and civic engagement for both individuals and communities at the local level would have the potential for growth and empowerment [19]. Higher levels of response from the authorities to residents' complaints would be associated with higher levels of citizens' confidence and participation [30].

It is believed that a feeling of belonging can have a catalytic effect on local action and development participation, which could later influence social relations, one's perception of the environment, and one's sense of control and empowerment within their community [7]. Policymakers and practitioners must remain aware of the importance of the use of neighborhoods as organizing and action units that can be used to achieve effective results [21]. This study aims to facilitate a better reading and interpretation of neighborhoods through the spatialization of community participation. In this sense, it is arguable to consider a neighborhood to be a social, spatial, and experiential unit that can be applied to a variety of programmatic challenges [21].

1.3. Understanding Social Aspects of Neighborhoods through Big Data

A detailed view of the conditions across a city can be obtained using administrative data such as the 311 system, 911 calls, and building permit applications. The Boston Area Research Institute and the City of Boston have leveraged the information provided by these data to develop methodologies that can be translated into econometrics, which are measures of the physical and social characteristics of neighborhoods [42]. This big data approach is likely to be a more sophisticated and cost-effective approach than the traditional surveys and observational protocols that have been used in the past.

A 311 service is more than just a way to register complaints; it introduces a concept of collaboration for the maintenance of the public spaces and infrastructures of a community. Using the system, citizens can report public issues like cracked sidewalks and graffiti, which helps the city's services allocate their resources efficiently and effectively.

By identifying and reporting such issues, citizens are acting as the city's eyes and ears [43]. The 311 system offers the opportunity to analyze how individuals report, including the quantity, type, and geographical distribution of these reports, providing detailed measures of reporting behavior.

The 311 data can be used to describe the different places where individuals have reported the same issues. Such calls are probably made by individuals who feel that they have a responsibility to the area in which they live and are eager to be involved in developing their community. With the advent of the 311 system, it becomes possible to measure the physical and social characteristics of neighborhoods. In this research, 311 requests for non-emergency issues are used to examine when and where people report such issues, and which neighborhoods within the City of Boston are reporting the same problems.

In the next section, the results of the community involvement in connecting the different neighborhoods within the city were analyzed, linked, and visualized. The proposed discussion moves to explore how these linkages and other dimensions can be helpful to the authorities when it comes to neighborhood development and resolving problems.

2. Materials and Methods

2.1. Materials

In order to conduct this research, the data provided by the Boston Area Research Initiative (BARI) and the 311 system for 2021 were utilized. They are a census tract-level dataset that was created to describe the features of neighborhoods, such as what issues people report and where and when they report them. Hence, the dataset that was used is a 9x6736 matrix.

According to the BARI 311 Database documents, which describe the structure and the organization of the database generated by the City of Boston's 311 system, Table 1 shows the following attributes for each record:

- BG_ID_10 is the unique identifier in BARI's GIS database for the census block group in which the address or intersection of the event is located (based on 2010 census geographies).
- TypCust is a count of the typical custodians estimated to reside within that geography (based on home locations; defined as an individual who reported two or fewer public issues in that calendar year).
- Exemplars are a count of the exemplar custodians estimated to reside within that geography (based on home locations; defined as individuals who reported three or more public issues in that calendar year).
- Year From 2010–2018 is indicated as the year the observation (call report) was administered.
- Custodianship reflects the likelihood that the residents of a neighborhood would use the 311 system to report issues in the public domain (e.g., potholes).
- Engagement reflects the likelihood that the neighborhood residents know of and would use the 311 system when in need.
- PublicDenig is a higher-order grouping that includes the two categories of case types that reference instances of public denigration: graffiti and trash.
- PrivateNeglect is a higher-order grouping that includes the three categories of case types that reference instances of private neglect: uncivil use, housing, and significant buildings.
- Housing indicates items that refer to poor household maintenance (e.g., poor heating and chronic dampness) and pests (e.g., bedbugs).
- UncivilUse indicates items that reflect the private actions that can negatively impact the public sphere (e.g., illegal rooming houses and poor property conditions).
- BigBuild indicates case types regarding problems with the upkeep of big buildings, like condos.
- Trash indicates incivilities regarding trash disposal (e.g., illegal dumping).
- Graffiti indicates requests for graffiti removal.

Table 1. Sample of the input data.

BG_ID_10	TypCust	Exemplars	Year from 2010–2018	Custodianship	Engagement	PublicDenig	PrivateNeglect	Housing	UncivilUse	BigBuild	Trash	Graffiti

In detail, on the one hand, BARI seeks to spur original, cutting-edge research within the greater Boston area that advances urban scholarship and improves public policy and practice. It is an inter-university research partnership between Northeastern University and Harvard University, in conjunction with the City of Boston. The mission of this institute relies on four pillars: (1) research–policy partnerships that focus on addressing the opportunities and challenges facing greater Boston communities, using a cross-disciplinary and data-driven approach, (2) The Boston Data Portal making new data sources accessible to researchers, policymakers, and practitioners of all levels of data literacy, (3) educational programming that provides data scientists and non-data scientists with the tools and skills necessary to work with community-based data, and 4) convening and supporting a thriving civic data community in greater Boston by organizing an annual conference, funding graduate student research, and conducting workshops for the development of "civic research agendas."

On the other hand, 311 is a non-emergency phone number that people can call in many cities, including Boston, if they need information about services, want to complain, or want to report graffiti or road damage.

BARI has worked closely with the 311 system to examine how Bostonians contribute to the maintenance of the public space and infrastructure in their neighborhoods. By using this dataset, it was possible to examine the characteristics of these neighborhoods and group them according to their needs.

2.2. Methods

To provide more interpretable results for this research, the census tract-level (CT) was aggregated into 23 neighborhoods. The dataset was first transformed from the CT levels to ZIP code levels, and then to neighborhoods. Through this process, it was encountered that a few CTs were located within 2 ZIP codes. In this case, the cross-boundary CTs were aggregated with the ZIP code that had the most registered data. Subsequently, 96% of the CTs were named correctly, and 4% were approximately connected to the closest neighborhood.

The data had different variables regarding each aspect that was included in this study. This paper concentrated on understanding the complaints of the whole neighborhood. Therefore, the investigation led to reducing all the variables into the nine components registered by 311 call centers. To do so, the principal component analysis (PCA) algorithm was employed. Reducing the number of variables in a dataset could cause inaccuracy, but a PCA helps to reduce the data while saving its accuracy. This method is based on an eigenvector value detection process. At the same time, the covariance matrix calculation plays a significant role in selecting which component of the call center data could be considered as the power. The balance is selected as the second eigenvector value, and the rest of the seven components hold the principle weight of less than 10%. Formula 1 shows how this step forms the complex dataset as interconnected value coordinates [44].

$$PCA\ value\ X = \frac{x_i - \sum_{i=1}^{n} x_i}{\sigma} \quad (1)$$

where:

X is the PCA value,
x_i is a single point in data set,
n is the maximum number of points and
σ is the standard deviation.

By identifying the main pillars of the dataset, its main values are identified, making use of the accessibility of the information to enhance the reliability of the conclusions that can be drawn from the dataset. A dataset, as described earlier, was used to collect all the transactions between citizens and the 311 system, and to identify not only the most frequent, but also the most distinguishing reasons, and to map them to their most accurate accuracy, so that further steps could be taken to give weight to the significant values. It is in this first step of the process that researchers uncover the necessary data to produce a neighborhood-level diagnosis, and after this, they contribute to the efforts to cluster and network the neighborhoods.

The next step in this research methodology, a cluster analysis based on the K means algorithm, was formed. This method was used to identify the groups of the neighborhoods based on their needs. The pursued attempt was to find the most homogeneous partitions, where the highest similarity or the lowest distance was observed while considering the difference to other neighborhoods. For this reason, the correlation distance method, with to respect the eigenvalues and grasped in the previous step to avoid biases, was used. This iterative process started with an arbitrary K value (the number of clusters), and employed the elbow method and the optimum value of the K for each year that was tested. Determining the optimal number of clusters, denoted as Optimum-K, is crucial in partitioning data points effectively. Selecting a number of clusters greater than the Optimum-k can lead to discrete clusters that contain members without a strong logical connection. Conversely, if the number of clusters is less than the Optimum-k, noise may exist within each cluster, resulting in a need for higher convergence to reach the same conclusion. Several tests can be used to determine the Optimum-k, such as the silhouette test, which was employed in this study. This test involves multiple random clusterings of the data points to determine whether the convergence of the points within each cluster is higher than their dissociation outside of it. A high silhouette score indicates that the points inside each cluster are optimally similar while being different from those outside. Thus, the Optimum-k provides a balance between an effective partitioning of the data points and the minimization of the presence of noise within the clusters. This K value fluctuated between the years, but the final result for each year's K means showed that the algorithm had been tested for the most reliable and accurate value via the silhouette test method. Following this is a step-by-step explanation of the K means clustering algorithm, the K determination, and the K evaluation.

K means cluster (Formula (2)): the approach that the K means follows to solve the problem is called expectation–maximization.

$$J = \sum_{i=1}^{m} \sum_{k=1}^{K} w_{ik} \|x_i - \mu_k\|^2 \quad (2)$$

where:

w_{ik} = 1 for data point x_i if it belongs to cluster k; otherwise, w_{ik} = 0.
μ_{k} is the pc of x_i's cluster.

In other words, the data point $\mathrm{x_i}$ is assigned to the closest cluster, judged by its sum of squared distance from the cluster's centroid.

The E-step is the assignment of the data points to the closest cluster. The M-step is the computation of the centroid of each cluster [45].

The initial stage in achieving the anticipated maximum involves two key variables, namely the E-step and the M-step. During the E-step, each data point is allocated to the nearest cluster, while in the M-step, a centroid is created for each cluster. These processes are interconnected, with the former step separating the clusters based on the inter-point distance in the dataset, and the latter step utilizing the within-cluster sum of squares (WIK) as a third variable, in order to determine the cluster boundary. Specifically, a data point is included in a cluster if its distance from the centroid is less than the distance between the centroid and the boundary, thus delineating the boundaries of each cluster. Overall, this nested approach is pivotal to optimizing the clustering process by accurately assigning the data points to their respective clusters, and enabling the computation of the cluster centroids and boundaries.

K determination (Formula (3)): The elbow method runs K-means clustering on the dataset for a range of values for k (say from 1–10), and then for each value of k, it computes an average score for all the clusters. By default, the distortion score is computed as the sum of square distances from each point to its assigned center.

$$\frac{\vartheta J}{\vartheta w_{ik}} = \sum_{i=1}^{m} \sum_{k=1}^{K} \|x_i - \mu_k\|^2 \Rightarrow w_{ik} = \begin{cases} 1\ if\ k + argmin_j \|x_i - \mu_j\|^2 \\ 0\ otherwise. \end{cases} \tag{3}$$

where:

w_{ik} is the centroid location,
x_i is a single point in data set,
μ_k is the pc of x_i*'s* cluster.

Performance analysis (Formula (4)): a silhouette analysis can be used to determine the degree of separation between the clusters. For each sample, the average distance from all the data points in the same cluster is computed (a_i). The average distance from all the data points in the closest cluster is computed (b_i). The coefficient is computed:

$$\frac{b_i}{max(a_i, b_i)} - \frac{a_i}{max(a_i, b_i)} \tag{4}$$

where:

b_i and a_i are arbitrary data points.

For finding logical patterns between the appropriate clusters from 2010–2020, the logical patterns between the neighborhoods of subsets have been examined. The association rule mining was used (see Formula (5)). Usually, this method is applied to find a meaningful pattern among the purchases from online stores. It is based on the items in a duplicate transaction in a series of transactions at a particular time. In this way, the items appear in the same subsets when the tendency for having them together is higher than average (support value). This research applied this method within each year's clusters to map the neighborhoods that have coexisted together for eleven years. The probability was calculated based on the density of the occurrence, and was then compared to the suggested threshold for the relevant significant level (see Formula (5)). This method is the base for the second step. As will be discussed over the resulting unit, the repetition of this two times made the distinction as clear as the third level that was considered as the selection between a polarized probability (more than 85% to 15%). Using this method, a proximity matrix will be generated that indicates the probability of coexistence between the 23 neighborhoods.

$$Supp(A \to B) = |\{t \in D | A \cup B \subseteq t\}||D| \tag{5}$$

where:

Supp is the support value;
A is the antecedent of the rule in the form of an itemset;
B is consequent in the form of an itemset;

t is a transaction containing A and B;
D is the total transaction.

$$Sup(d) = n(d)\ /\ |D| \tag{6}$$

$$Util(d) = Sup(d) \times U(d) \tag{7}$$

$$avesup = \frac{\sum U_{til}(d)}{d}|N| \tag{8}$$

$$min_{sup} = ave_{sup}\ /\ |D| \tag{9}$$

where:

Sup(d) = the support value for an item;
n(*d*) = the number of occurrences for an item;
∣*D*∣ = the total transaction;
∣*N*∣ = the total item;
U(d) = the utility value for an item;
$U_{til}(d)$ = the utility and support value for an item;
Ave_{sup} = the average utility of the item;
Min_{sup} = the minimum threshold value (item density level).

The last step in this methodology involves using a network analysis [46,47]. The network is undirected and aims to connect the communities based on the clusters found in the previous step. In the networks, nodes represent neighborhoods, and line weights refer to the probability of coexistence. After forming all ten networks, the betweenness centrality was calculated as an index for the neighborhoods' roles towards each other when it came to non-emergency issues. Furthermore, the clustering coefficient value was calculated as an index for the homogeneity level of the network. For this step, Gephi software was employed. Below, the betweenness centrality measurements and the clustering coefficient (see Formulas (10) and (11)) were calculated.

$$b_i = \sum s < tg_i(st)/nst(1/2)n(n-1) \tag{10}$$

where:

n is the total number of vertices in the network,
gi(st) is the number of geodesic paths from vertex s to vertex t that pass through *i*
nst is the total number of geodesic paths from *s* to *t*.

The clustering coefficients [48]:

$$C_i^{wei,B} = \frac{1}{s_i(k_i-1)} \qquad \sum\nolimits_{1 \le j,\ l < N_{ROI}} \frac{w_{ij}+w_{jl}}{2}\ a_{ij}a_{il}a_{jl} \tag{11}$$

where:

$s_i = \sum_{j=1}^{N_{ROI}} w_{ij}$ is the node strength (i.e., the weighted degree). It should be noted that *aijailajl* = 1 if nodes I, j and l form a triangle in the unweighted network. Otherwise, $a_{ij}a_{il}a_{jl}$ = 0. The average of $C_i^{wei,B}$ over all the nodes defines the global weighted clustering coefficient, which is denoted by $C^{wei,B}$.

3. Results

The first result of this study addressed the PCA analyses of the City of Boston at the neighborhood level. Table 2 shows the nine essential characteristics of the Bostonian communities that reported to 311 centers. As shown, the custodianship as a factor of citizen safety satisfaction varies from 1.52 in Beacon Hill, historically known as a well-served community, to −0.08 in Fenway Kenmore, which shows the non-satisfaction of this neighborhood's residents. Similarly, Fenway Kenmore is the lowest for the engagement component (−0.66). However, the highest (1) was in West Roxbury, recently known as an emerging prestige neighborhood of Boston. Within the engagement component, 5 negative observations are made compared to 18 positives, emphasizing a 1.66 range of disparity.

Table 2. PCA analyses of the nine characteristics of Boston's neighborhoods reported to 311 call center for 2020.

	Neighborhood	Custodians	Engagement	Public Denig	Private Neglect	Housing	Uncivil Use	BigBuild	Trash	Graffiti
1	Brighton	0.26	0.23	0.28	0.29	0.24	0.23	0.05	0.25	0.14
2	Allston	0.07	−0.21	0.44	0.49	0.57	0.18	0.14	0.26	0.53
3	Fenway_Kenmore	−0.08	−0.66	0.21	−0.15	−0.12	−0.18	0.06	0.08	0.29
4	Back Bay	0.84	0.33	0.32	0.12	0.02	0.12	0.02	0.26	0.27
5	Beacon Hill	1.52	0.78	0.22	0.24	0.24	0.16	0.08	0.18	0.12
6	West End	0.42	−0.26	0.23	−0.1	−0.08	−0.12	−0.01	0.17	0.2
7	North End	0.8	0.4	0.39	0.05	−0.02	0.1	0.04	0.36	0.24
8	Downtown	0.92	0.3	0.34	0.1	0.06	0.13	0.01	0.3	0.21
9	Charlestown	0.4	0.27	0.18	0.02	−0.01	−0.01	0.04	0.17	0.1
10	South Boston	0.26	0.13	0.12	0.09	0.01	0.05	−0.02	0.11	−0.02
11	South End	0.93	0.28	0.35	0.41	0.45	0.22	0.04	0.32	0.21
12	Wharf District	1.32	0.29	0.29	0.25	0.15	0.22	−0.1	0.23	0.22
13	Chinatown	0.64	−0.39	0.43	−0.04	−0.14	0.09	0.04	0.29	0.49
14	Roxbury	0.49	0.27	0.26	0.32	0.35	0.17	0.04	0.19	0.25
15	East Boston	0.09	−0.12	0.29	0.25	0.2	0.25	−0.01	0.24	0.27
16	Mission Hill	−0.01	−0.35	0.25	0.35	0.43	0.1	−0.02	0.15	0.33
17	Jamaica Plain	0.1	0.11	0.05	−0.09	−0.15	−0.02	−0.03	−0.01	0.11
18	Mid-Dorchester	0.21	0.56	0.24	0.62	0.73	0.36	0.07	0.2	0.13
19	Dorchester	0.31	0.49	0.23	0.49	0.51	0.35	0.04	0.2	0.12
20	Mattapan	0.35	0.9	0.21	0.63	0.68	0.44	0.12	0.2	0.06
21	Roslindale	0.33	0.78	0.12	0.12	0.02	0.18	0.03	0.08	0.1
22	West Roxbury	0.5	1	0.14	0.13	0.01	0.18	0.02	0.13	0.05
23	Hyde Park	0.15	0.71	0.06	0.14	0.1	0.18	−0.01	0.05	0.01

With regard to Public Denig, it is a factor that shows to what extent citizens could rely on public authority for the community's development. Regarding this point, the resident's trust in 311 to solve their problems is assessed through a survey after each call or application notification. Although the value of this factor is positive in all the neighborhoods, Jamaica Plain has the lowest reported. Jamaica Plain is historically known as a place for immigrants and people of color. As stated by the Boston Resilience Strategy, these target groups have a difficulty connecting with authorized officials because of language barriers or cultural differences.

Another aspect is Private Neglect. This is a factor of the buildings, areas, or objects that have been left untouched for a long time within a neighborhood, which is observed as neglected gray areas for the community. Usually, this factor comes from notifications that requested for the collecting or reusing of objects and areas. Mattapan, Mid-Dorchester, and Dorchester have the highest concentration of this aspect. These neighborhoods hold a long history of gray areas and left-behind zones, which are currently driving the attention of tremendous knowledge-intensive companies for investment and land use conversion. Mattapan, which has the highest value of Private Neglect (0.63), is transforming into a biopharmaceutical hub of the eastern coast in the most southern part of Boston, benefiting from relatively large gray areas that are facilitated by commuter trains and highways.

Housing complaints and neighborhood issues such as snowfalls are the most frequent 311 reports, followed by Private Neglect. For this reason, this point was analyzed. However, these neighborhoods have a relatively high engagement. The Wharf District and the downtown area have a negative score for housing issues. Nevertheless, the density of the living area in these neighborhoods is lower compared to the business land use.

Uncivil Use is a legal term for the utilization of facilities for illegal or non-appropriate functions. Complaints such as a loud neighbors, who are offensive during the quiet period of a neighborhood, changing land use (especially from residential to business), or smuggling acts in public fall under the Uncivil Use aspect. Fenway Kenmore, West End, Jamaica Plain, and Charlestown have the lowest values in the City of Boston. These issues, as stated earlier, are more frequent in communities with recent demographic changes. For example, Fenway Kenmore has numerous international students due to its affordable rent and Jamaica Plain is one of the most diverse areas of Boston. Additionally, West End has pioneering and diverse communities known as European immigrant hosts.

Big Building is a factor of the complaints for the high-density, high-rise buildings that report mis-management. Interestingly, Wharf District, known as the financial district, has the lowest score. The area has many towers, business buildings, offices, and parking. This score demonstrates the low satisfaction of the residents and businesses located in the area due to low service infrastructure, especially on severe climate days. The most frequent complaints made were regarding the traffic, elevators, and snow dumps. On the other hand, Allston has the highest score, which is expected, since the neighborhood is well-served by community management buildings.

Trash is a common issue in downtown Boston in areas such as Back Bay, North End, Beacon Hill, and the South End areas, with the highest score in North End due to its busy food and beverage retails, followed by South End, Downtown, and Chinatown, with 0.36, 0.32, 0.30, and 0.29, respectively. These neighborhoods lack residents and most of their areas are furnished for retail shops, restaurants, and small-medium businesses. Their community levels are disconnected; the most apparent indicator of this phenomenon is the trash collection issues.

Lastly, the Graffiti issue is considered to be a typical issue in Boston, and it was found that the neighborhood level cannot serve as the best indicator for this, since each neighborhood faces this issue, but, in some instances, specifically in mis-served spots. As discussed earlier, the areas with a high proportion of diversity and multicultural residents have more reports about Graffiti. However, other areas such as Brighton, Hyde Park, and Downtown also reported Graffiti.

The following step was applying the elbow method. Figure 2 shows that, despite the homogenous distribution of the factor values across the neighborhoods, the K value seems to fluctuate from neighborhood to neighborhood. The most significant difference occurred in 2019, a year prior to the pandemic.

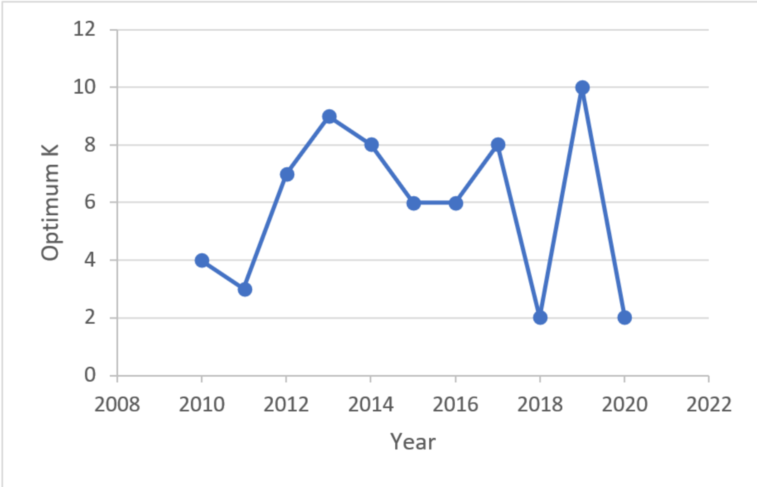

Figure 2. Elbow method that shows the optimum K value in each year from 2010 to 2020.

The elbow method is utilized to find the optimum K for the clustering step. Ks above the elbow indicate the number dividing the data into infinite subgroups with no possible definition, while Ks less than the elbow neglect the significant differences in the data, thus weakening the clustering effect. The optimum clustering phase is dependent on respecting any K that corresponds to the period/category of selection.

On the other hand, one of the objectives of this research is to visualize clusters. The silhouette method was conducted to show the clusters based on the correlation distance measure (see Figure 3). The analysis shows that the number of clusters declined to only 2 in 2018 and 2020 (Figure 3i,k). It is due to this variety of partitioning that the K-means algorithm generates multiple clusters out of the data. In 2013 and 2019, there are clusters in the city with only one neighborhood (Figure 3d,j). It shows that 2019 had the highest level of disparity in the city. The center of each cluster is located at the farthest possible position from the rest, which means that in 2011 and 2018, when the 23 neighborhoods were divided into two and three clusters, respectively, the city experienced a significant polarization in terms of its residents' social and physical complaints.

Our method reveals clusters whose areas are twofold larger than the others in the analysis. Based on our analysis, the large-shape clusters (measured by area, not by the number of members) are more likely to be interpreted as fragile. According to the silhouette method used for the performance assessment results, the clusters with linear shapes score higher than those with large polygons. In addition, the cluster centers are determined by the weighted average distance between the neighborhoods. In 2017 and 2019, results were observed by the authors with centers that were very close to each other, with eight and ten centers densely located, respectively (Figure 3h,j). Conversely, in 2013, there were nine centers, and their distances were fairly normal (Figure 3d). This method is considered to be an innovative way for evaluating clustering and analyzing the results.

As stated earlier, the clusters fluctuated during the ten years of the study; thus, an association rule analysis was used to find out which neighborhoods were most likely to appear together during the mentioned period. For this reason, a step-by-step algorithm was conducted, in which Table 3 shows the first layer of the results. Then, the specified threshold that was explained in the methodology was applied to explore the results more conclusively. The highlighted cells are the coexistence with the relevant probability (more significant than the threshold). These values are the ones that will be used in the second layer of the study.

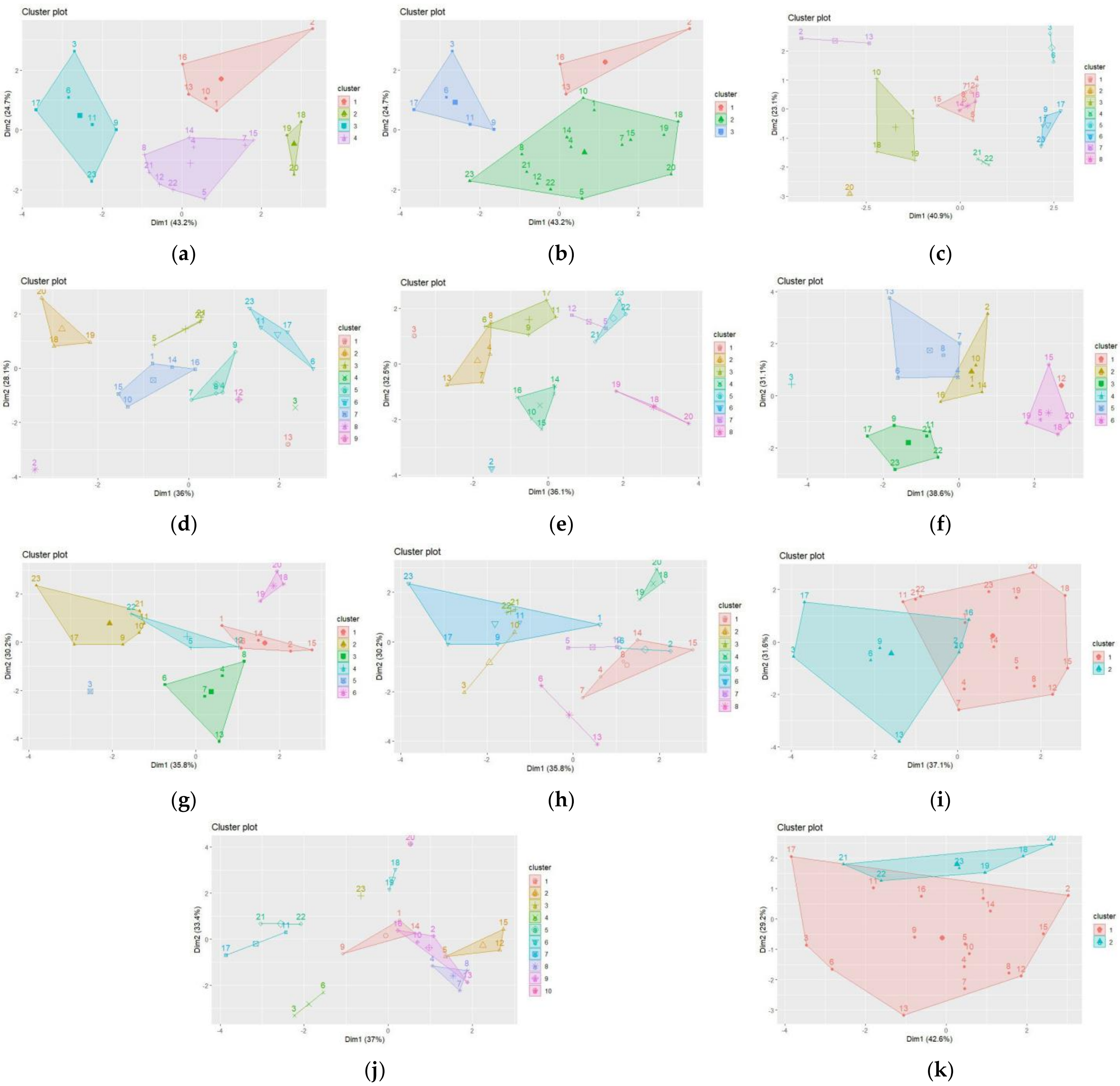

Figure 3. Neighborhood clusters based on PCA factors of 311 nonemergency system. Each graph shows each year's clusters based on the correlation distance measure. Colors represent the clusters while variety of shaded areas represent the size of the cluster. The figures are for years from 2010 to 2020. Starting by (**a**) for 2010, (**b**) is 2011, (**c**) 2012, (**d**) 2013, (**e**) 2014, (**f**) 2015, (**g**) 2016, (**h**) 2017, (**i**) 2018, (**j**) 2019, and (**k**) 2020.

Table 3. First layer association rule probability matrix.

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
1	**1.00**	0.36	0.09	0.00	0.27	0.18	0.00	0.00	0.00	0.64	0.00	0.27	0.18	0.73	0.64	0.45	0.00	0.27	0.36	0.18	0.18	0.18	0.27
2	0.36	**1.00**	0.09	0.09	0.09	0.00	0.09	0.09	0.18	0.36	0.09	0.09	0.55	0.27	0.18	0.64	0.18	0.00	0.00	0.00	0.00	0.00	0.00
3	0.09	0.09	**1.00**	0.00	0.00	0.55	0.00	0.00	0.36	0.00	0.27	0.00	0.18	0.00	0.00	0.00	0.36	0.00	0.00	0.00	0.00	0.09	0.00
4	0.00	0.09	0.00	**1.00**	0.27	0.27	1.00	1.00	0.18	0.00	0.18	0.36	0.00	0.36	0.45	0.00	0.00	0.18	0.18	0.18	0.27	0.27	0.18
5	0.27	0.09	0.00	0.27	**1.00**	0.00	0.36	0.45	0.00	0.00	0.18	0.82	0.00	0.36	0.64	0.00	0.00	0.27	0.27	0.27	0.36	0.36	0.18
6	0.18	0.09	0.55	0.27	0.00	**1.00**	0.00	0.00	0.45	0.18	0.55	0.00	0.45	0.00	0.00	0.18	0.45	0.00	0.00	0.00	0.00	0.00	0.00
7	0.00	0.09	0.00	1.00	0.36	0.00	**1.00**	1.00	0.18	0.18	0.18	0.00	0.27	0.36	0.00	0.09	0.09	0.00	0.00	0.00	0.00	0.18	0.18
8	0.00	0.09	0.00	1.00	0.45	0.00	1.00	**1.00**	0.00	0.18	0.18	0.45	0.00	0.45	0.55	0.00	0.00	0.18	0.18	0.18	0.27	0.27	0.18
9	0.00	0.18	0.36	0.18	0.00	0.45	0.18	0.00	**1.00**	0.27	0.73	0.00	0.00	0.00	0.00	0.18	0.82	0.00	0.00	0.00	0.09	0.18	0.36
10	0.64	0.36	0.00	0.18	0.00	0.18	0.18	0.18	0.27	**1.00**	0.18	0.00	0.36	0.45	0.00	0.73	0.27	0.18	0.18	0.00	0.18	0.09	0.18
11	0.00	0.09	0.27	0.18	0.00	0.55	0.18	0.18	0.73	0.18	**1.00**	0.18	0.18	0.18	0.18	0.00	0.91	0.09	0.09	0.09	0.27	0.27	0.55
12	0.27	0.09	0.00	0.36	0.82	0.00	0.45	0.45	0.00	0.00	0.18	**1.00**	0.00	0.27	0.55	0.00	0.00	0.18	0.18	0.18	0.27	0.36	0.18
13	0.18	0.55	0.18	0.00	0.00	0.45	0.27	0.27	0.00	0.36	0.18	0.00	**1.00**	0.09	0.00	0.45	0.00	0.00	0.00	0.00	0.00	0.00	0.00
14	0.73	0.27	0.00	0.36	0.36	0.00	0.36	0.45	0.18	0.45	0.18	0.00	0.00	**1.00**	0.73	0.55	0.09	0.18	0.18	0.18	0.27	0.27	0.18
15	0.55	0.18	0.00	0.45	0.64	0.00	0.45	0.55	0.00	0.00	0.18	0.55	0.00	0.73	**1.00**	0.00	0.00	0.27	0.27	0.27	0.18	0.27	0.18
16	0.45	0.64	0.00	0.00	0.00	0.18	0.09	0.00	0.18	0.73	0.00	0.00	0.45	0.55	0.00	**1.00**	0.18	0.00	0.00	0.00	0.00	0.00	0.00
17	0.00	0.18	0.36	0.00	0.00	0.45	0.09	0.00	0.82	0.27	0.91	0.00	0.00	0.09	0.00	0.18	**1.00**	0.00	0.00	0.00	0.18	0.18	0.36
18	0.27	0.00	0.00	0.18	0.27	0.00	0.18	0.18	0.00	0.18	0.09	0.18	0.00	0.18	0.27	0.00	0.00	**1.00**	0.91	0.73	0.18	0.18	0.18
19	0.36	0.00	0.00	0.18	0.27	0.00	0.18	0.18	0.00	0.18	0.09	0.18	0.00	0.18	0.27	0.00	0.00	0.91	**1.00**	0.82	0.27	0.27	0.00
20	0.18	0.00	0.00	0.18	0.27	0.00	0.18	0.18	0.00	0.00	0.09	0.18	0.00	0.18	0.27	0.00	0.00	0.73	0.82	**1.00**	0.27	0.27	0.27
21	0.00	0.00	0.00	0.27	0.36	0.00	0.27	0.27	0.09	0.00	0.27	0.27	0.00	0.27	0.18	0.00	0.00	0.18	0.27	0.27	**1.00**	0.27	0.55
22	0.18	0.00	0.09	0.27	0.36	0.00	0.18	0.27	0.18	0.00	0.27	0.00	0.00	0.00	0.27	0.00	0.00	0.18	0.27	0.27	0.91	**1.00**	0.45
23	0.27	0.00	0.00	0.18	0.18	0.00	0.18	0.00	0.36	0.18	0.55	0.18	0.00	0.18	0.18	0.00	0.36	0.18	0.00	0.27	0.55	0.45	**1.00**

Figure 4 shows the frequency for the neighborhoods with relevant connections, and this analysis shows the pattern of the connectedness between the areas of the city in terms of their community problems. As illustrated, neighborhoods 6 and 7 are the only areas that can be interpreted clearly, as they appear in a few clusters with the same connections. However, the rest of the 21 neighborhoods have more than eight observed connections that are higher than the threshold probability. This required a deeper analysis to get a better understanding of the results. For this reason, the second layer of the association rule algorithm was conducted, fixing two neighborhoods and permuting the rest of the relevant chances to find out if there is any probability of finding the relevant pattern (Table 4). In the second layer, it was found that the chance for coexistence is not a random connection, but that specific neighborhoods are connected conditionally.

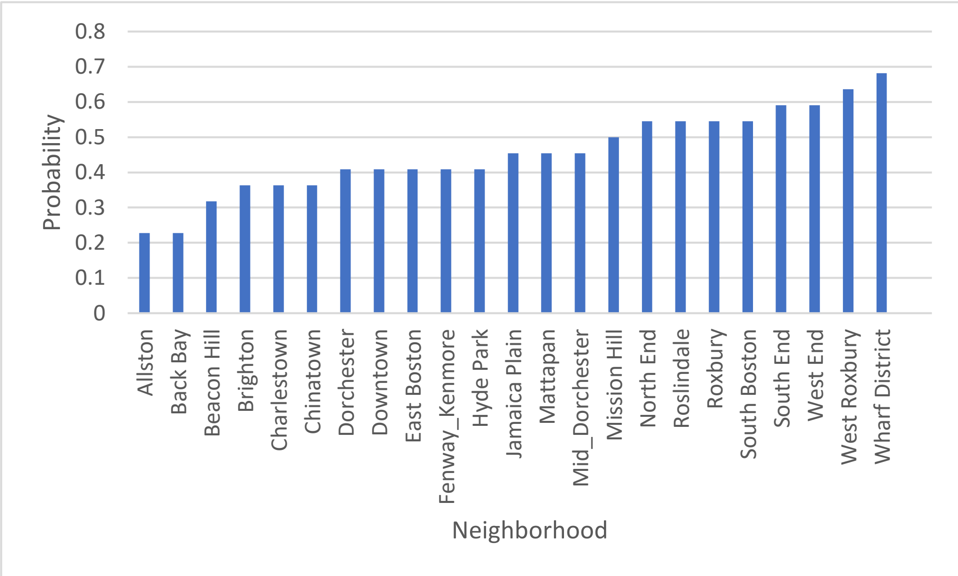

Figure 4. Histogram for first layer connection probability.

Table 4. A sample of the second layer of the association rule probability.

First Layer		Second Layer	Probability
Back Bay	North End	Downtown	1.00
Back Bay	Downtown	North End	1.00
Allston	Chinatown	Mission Hill	0.55
Back Bay	South End	North End	0.45
Back Bay	South End	West End	0.45
Beacon Hill	Wharf District	South End	0.66

Neighborhoods appear together in a rational pattern. It was found that, in assuming two areas as Neighborhood 1 (N1) and Neighborhood 2 (N2), there are comparable and calculatable chances for a third member of this subgroup, as explained in Table 4. Although the call center contacts are arbitrary at first glance, the pattern for the coexistence of N1, N2, . . . , and N23 is well structured. For example, assuming that Back Bay and North End are in a cluster, Downtown follows as the next cluster component, defining the same applicable results (see Table 3). This example is geographically proven, since the three areas are connected in the Boston area. However, that was not the case in many other neighborhoods. The non-geographically connected neighborhoods lead to the drawing of the adjacency matrix to show the network outcome.

The two-phase algorithm that was applied for the connection probability enhanced the network mapping, in order to define an index that illustrated the connection weights. As stated earlier, the neighborhoods are connected, advocating for the same issues in a city context. The level of this connectedness with the network of connection was determined by introducing the former mechanism, in which N1 is connected to N2 if they appear above the threshold number of times. The network generated as an outcome of this process demonstrates which neighborhoods could be considered to be interconnected, even if non-geographical proximity is observed.

At the tail of Figure 5, the West End and North End neighborhoods are observed. The degree of this area is proportional to the area of the neighborhoods and their context. Although many other neighborhoods in Boston, such as Chinatown and Downtown, have many restaurants, North End is concentrated on dining and beverage services comparted to the population density, and is well-prepared for retail services. Thus, the residents' complaints have less in common with the rest of the city, followed by the West End district as the financial and accommodation services hub of Boston.

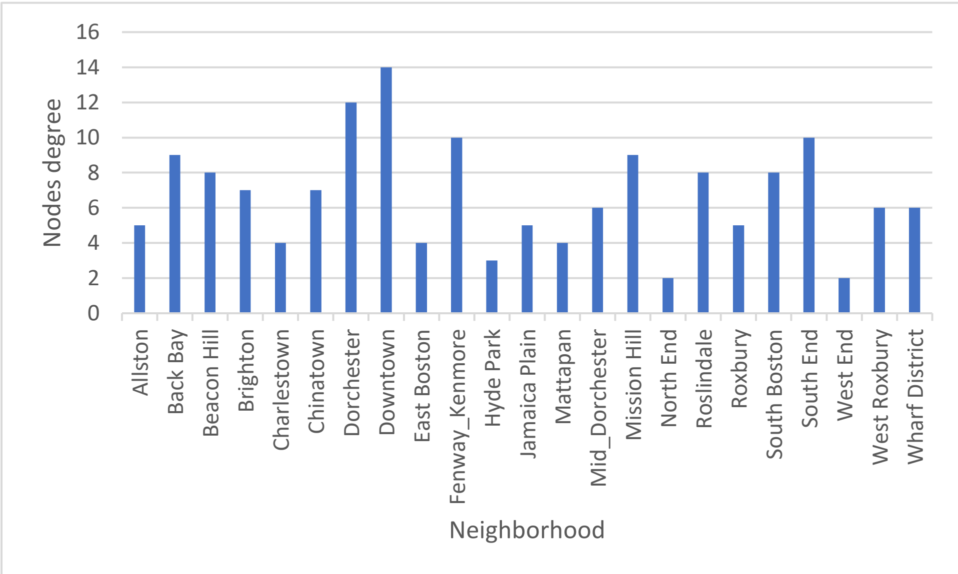

Figure 5. Neighborhoods nodes degree on 311 network.

The last step was to conduct a network analysis. The first finding of the network study for the clusters of Boston shows that the network density is relative to what was expected (0.391) with 23 nodes. As illustrated in Figure 6, Downtown, with 14 connections, is connected to almost 63% of its potential connections, which indicates that this neighborhood has common problems with the other neighborhoods. The nodes' degrees are well distributed; however, the left skewness is observed. Compared to other types of urban networks, this arrangement is very important to describe the neighborhood clustering tendency from a different perspective.

By mapping the network through the lens of closeness centrality (Figure 6), it is possible to detect which neighborhoods are central in Boston. South End, West Roxbury, and Back Bay have the highest closeness, respectively. Considering the analysis, this information can be translated into the primary resident hub for the location. South End is an important residential area as it is home to the BU medical campus and Northeastern University campus, and thus includes many residential complexes to accommodate the students and staff of these organizations. A prominent voice for 311 is found here in the downtown area. As the network illustrates, West Roxbury is located at the southwestern border of Boston, and aims to advocate for the neighborhoods located west and south of the city. As the network demonstrates, neighborhoods were grouped based on the issues that they shared with the rest of the city. It could be argued that each neighborhood's closeness can be viewed as a result of its central role in terms of its members of the generated cluster. South End is historically known as the central hub of Boston, housing middle-class residents and commuters from Massachusetts, and is expected to play a central role in resolving typical problems. As the degree graph (Figure 6) proves that the degree for this node is above average (9 > 6.8), the connections and centrality are explainable.

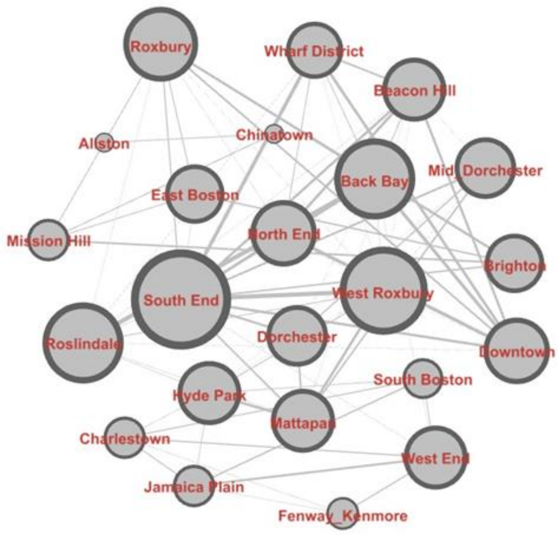

Figure 6. Closeness centrality of 311 aspects.

Betweenness centrality typically measures the shortest path in a network. Within this research context, the centrality measures the flow of the issues within the network. As illustrated in Figure 7, South End, Mission Hill, Roxbury, and West End are the neighborhoods that have the highest participation in the 311 system. The mentioned districts are the ones that connected the clusters during the ten years of the research period. In this research, it is possible to argue that the neighborhoods with high degrees cannot necessarily know their connectedness to the network or their central point for playing as the bridge. As the network shows, Downtown and Dorchester are, relatively, the most isolated neighborhoods in terms of the 311 reports compared to other neighborhoods. Furthermore, it is also observable that the dominant nodes in the betweenness centrality are the neighborhoods that are ranked among the highest poverty rates, based on the Boston Socioeconomic database [49]. However, Allston, with a higher poverty rate than South End, is not ranked as one of the central components.

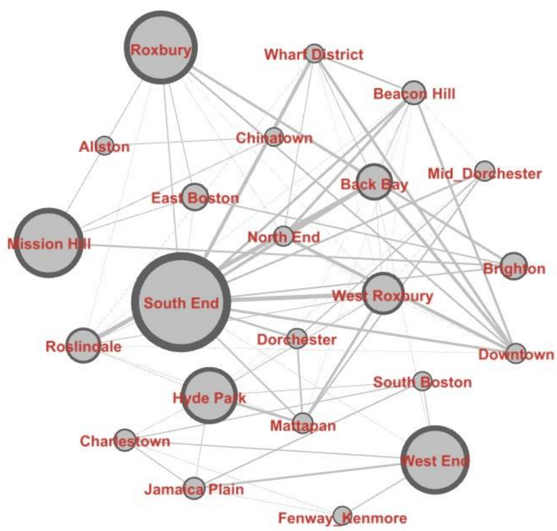

Figure 7. Betweenness centrality of 311 aspects.

In this chapter, methodological steps were implemented to find a possible proximity regarding the community issues that were shared with the 311 platforms. Neighborhoods are mapped in a systematic approach, in which a progressive process is applied to every single transaction enacted by the citizen to the city on its community scale. Developing such an algorithm helped in understanding more about the common problems of these neighborhoods. However, the focus of the methodology was on places instead of issues. Upon validating the network results with Boston socioeconomics, they are relatively consistent. Although the networks are generally known for being non-dimensional, the results showed that measures such as closeness and betweenness could provide a better glance at issues and emergency malmanagement.

4. Discussion and Conclusions

Our cities are facing ongoing challenges which could be utilized as opportunities for better urban development, and if not well-managed, they will turn into problems. Local government has a big role to play in strengthening resilience and improving urban transition at the local level. To be resilient, one must be able to respond more swiftly to daily stresses that might become chronic problems in the city. For example, the lack of adequate infrastructure and services, unsafe housing, and inadequate and poor health services can turn natural hazards into disasters. The poor management of solid waste can lead to flooding and waterlogging due to blocked storm and sewage systems. Water scarcity or contamination can be caused by the destruction or damage of infrastructure. A lack of access to safe housing, good sanitation, health care, and education affects the ability of urban residents to recover. It is, therefore, important to understand the capacity of communities and decision makers to actively cope with these potential challenges. In this regard, a key challenge for planning is being able to determine which innovative and transformative methods are most appropriate for dealing with these problems.

The default approach to defining neighborhoods involves the categorization of residents based on their income or access to facilities, which can be misleading. Moreover, living in the same neighborhood does not guarantee the uniformity of problems or needs. Instead, urban management should consider the shared structural weaknesses or risks among neighborhoods and respond accordingly. Most likely, the community's needs and behaviors play a role in connecting urban areas.

The current study proposed a model of testing the proximity between neighborhoods that does not only come from the geographic aspect. Proximity, or the closeness between different neighborhoods, can be described if two or more neighborhoods share the same social and physical needs. This paper tried to examine what the common social aspects are in different neighborhoods within the same city, and how they could be utilized in urban development processes.

The study focused on Boston due to its extensive network of neighborhoods, citizens, policymakers, and leaders, with the aim of considering dimensions beyond the traditional ones (e.g., geographic). Community participation programs can show the social needs of the local citizens. This neighborhood connection study found that the reporting of non-emergency issues to the 311 system can indicate a lot about the physical and social characteristics of neighborhoods.

In this study, the residents' complaints/reports relating to the same issues are analyzed across the city's neighborhoods. By using 311 data, it was possible to see the shared issues between neighborhoods, such as engagement, trash, and graffiti, and to classify the neighborhoods based on the similarities of their socioeconomic characteristics, behavior, and needs. With methods such as a PCA, K-means, association rule mining, network software, and degrees of centrality, the members of the clusters and crucial nodes in the network were identified. The results showed that there is a correlation between Boston neighborhoods in terms of their needs. The research reveals the level of connectedness between the neighborhoods that are known, as they are not geographically connected. It was shown that some neighborhoods can act as linking bridges for other neighborhoods, while others may be isolated within the network graph. The results show that, even if some neighborhoods are relatively far from each other, they might report the same complaints. For example, in South End and West Roxbury, people are paying the same attention to the same issue. A series of graphs that show which neighborhoods are linked based on their social concerns was generated.

Using this method, the mutual interests that are taking place in neighborhoods was demonstrated. This perspective can help to address urban problems in an innovative way. In other words, the same solution can be applied in different locations if the same type of problem is identified. This way, the same clustered neighborhoods can be monitored together, and further action can be taken in advance. Although urban areas are experiencing multiple shocks and stresses, a one-size-fits-all action plan might not work best for all places [24]. The authors believe that constant monitoring at the community level could result in better strategies being suggested and tailored to their own demands. An increasing number of complaints in a cluster can be a signal to authorities that a common problem is affecting different neighborhoods, which can increase the effectiveness of the response. This would facilitate the policymaking process.

The databases produced by 311 and other city service hotlines provide insight into the extent to which city residents address their communities' issues. By doing so, authorities will be in a better position to address various neighborhoods with the same approach, which will facilitate the policymaking process. In this regard, it is possible to see how modern technology ushers society into the era of big data, while bringing with it both challenges and opportunities for identifying and pursuing new insights.

The 311 system provides a remarkable opportunity for policy collaborations surrounding physical neighborhood maintenance. In the United States and Europe, such systems are becoming increasingly popular, as a part of an ongoing trend to improve service delivery by using technology. Chicago, New York City, Washington D.C., and Boston are some of these cities that make their data available to the public [50]. Such datasets provide scholars with the opportunity to conduct their own analyses, in the hope that this might lead to cutting-edge research. Moreover, having citizens participate in the development of their communities will allow authorities to better monitor the city. Hence, these reports work as a link between the government and the residents.

By conducting this study, the authors were able to define the concerns of individuals. In this way, it is possible to identify the areas or issues that require further investigation and intervention. Such a study is useful for city authorities to understand the types of issues that occur in the neighborhoods around the city. In this way, the connection or the proximity of the neighborhoods is considered and characterized by the types and frequency of issues that residents report. It can be considered a great way to understand the social aspects that characterize the city. It is important to identify these patterns of citizen behavior, identify the frequency with which people call, the issues they report, where the problems are reported, and what the demographic factors are.

The use of a real-time tool, such as the one described in this essay, can help to identify common risks across neighborhoods and prioritize the responses based on need. By categorizing people or communities based on shared risks, city managers can allocate resources to address the same problems in different neighborhoods. Through this approach, neighborhoods that may not have physical or geographical proximity, but share common risks, can be identified and addressed.

This perspective on city management can inform decision making at different levels, from city planning to addressing specific risks. The next step is to develop a unified network of risks that identifies the similarities among the different types of risks, and prioritizes investments based on the most common risks in the suitable neighborhoods. In doing so, city managers can gain the support and approval of citizens while addressing the most pressing needs of the community.

Author Contributions: Conceptualization, C.B. and P.S.; methodology, P.S.; software, P.S.; writing—original draft preparation, P.S. and N.H.; writing—review and editing, N.H., C.B., F.M. and P.S.; supervision, C.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research work is the result of the synergetic activity of the TREnD (Transition with Resilience for Evolutionary Development) Project, which received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreements no. 823952, and the SOUND (Smart Open Urban-rural iNnovation Data) Project that received funding from the Italian Minister of University and Research (MIUR) under the PRIN—Progetti di Ricerca di Rilevante Interesse Nazionale Bando 2017 grant no. 2017JMHK4F.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: All econometrics are available through BostonMap. They can also be downloaded with documentation from the Boston Data Portal, organized by source data set (e.g., 311, building permits). BARI releases a modified version of Boston's 311 data annually.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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