Neighbourhood characteristics and social network segregation: exploring the temporal dynamics of social interactions in residential environments, Trentino

Introduction and Assumption

Urbanization affects population density, accessibility, housing quality etc., the inequitable allocation generated in this process leads to socio-economic disparities, which results in spatially segregated cities (Han *et al.*, 2019; Pandey, Brelsford and Seto, 2022; Maparu and Mazumder, 2017). Residential segregation is one of the obvious phenomena (Schaeffer and Tivadar, 2019; Tehrani, Wu and Roberts, 2019). The unequal accessibility to education sources, amenity and services of residential segregation limits the horizons and social range of people, leading to social isolation (Preteceille, 1986; Briggs, 2005). This research aims to shed light on the relationship between social network segregation and neighbourhood characteristics, examining the temporal dynamics of Call Detail Records (CDRs) hotspot probabilities and network homogeneity in different neighbourhoods. Based on literature review, the assumption here would be: CDR network hotspots are more likely to be found in high quality neighbourhoods, which are more socially diverse (less homogeneous).

Methodology

As flow chart shown in Appendix 1, this study employs census data and Call Detail Records (CDRs) from Trentino to explore the interaction between neighbourhood characteristics and social networks. According to literature, census data depict neighbourhood characteristics, while CDRs are utilized to analyse social networks (Wu *et al.*, 2014; Maji, Mandal and Sen, 2023). CDRs data selected for one day on 6 November 2013.

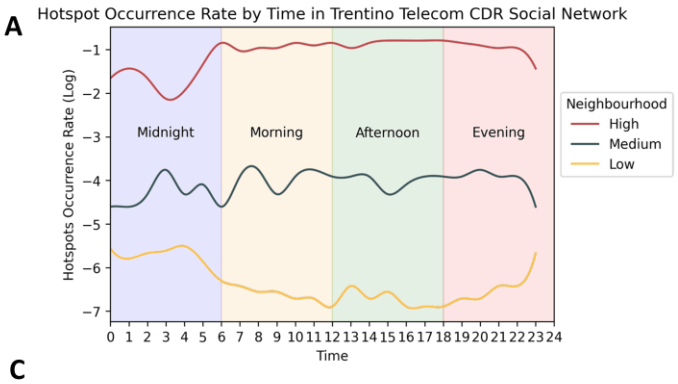
- **Census Data:** The study first aggregates census indicator data to grid scale by calculating the spatial intersection of census tracts and grid, following the equation in Appendix 2. PCA (principal component analysis) is then used to summarise the 6 components from more than 140 original variables (Appendix 3). After conducting K-means clustering, three neighbourhood groups are out. Each cluster reflects different levels of neighbourhood living quality. To make the subsequent study more convenient, the cluster with the highest percentage of radargrams is referred to as “High”, indicating the best neighbourhood, and the rest as “Medium” and “Low” (Appendix 4-6).
- **Call Detail Records (CDRs):** This study only considers the intra-city flows of CDRs between different girds in Trentino and does not consider the internal traffic of each grid, so the rows where the starting grid equal to targeted gird are removed. Then a threshold of 75th percentile is applied to reduce the number of edges to avoid oversize network.
- **Combing Analysis:** Neighbourhood clusters and CDRs social network are combined, using weighted K-shell centrality to identify network hotspots hourly across three neighbourhood types. Hotspots are defined as the top 30 in weighted K-shell centrality. To account for neighbourhood size differences, hotspot rates are calculated as the number of hotspots per total grid count. Time-specific homogeneity is analysed by calculating the EI Homophily Index for Midnight, Morning, Afternoon, and Night, to investigate the homophily dynamics of various neighbourhoods over time.

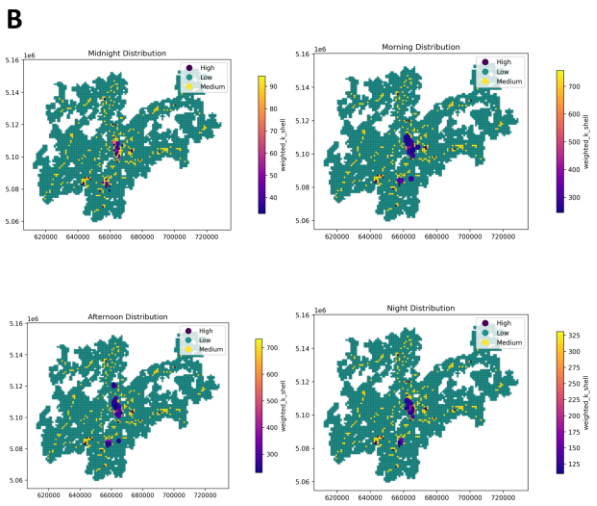
Result (Appendix 0)

- High-quality neighbourhoods have a significantly higher rate of hotspot appearances than other neighbourhoods, suggesting that neighbourhoods that are well-lived in and fast-growing play a more important role in social networks and that people have more social opportunities (Figure A).
- Relatively low hotspot rates at night in high-quality neighbourhoods and relatively high hotspot rates in low-quality neighbourhoods reveal urban flow dynamics, i.e. people travelling to high neighbourhoods during the day for work (Figure A).
- The social hotspots are primarily concentrated in the central and southern areas of Trentino. During peak social traffic periods, such as the afternoon, high-quality areas in the north also become hotspots. However, such occurrences are almost non-existent in other regions, revealing a geographical segregation in the social network (Figure B).
- A near +1 EI Homophily Index implies that people in high and medium quality communities are more inclined to interact with those from different areas, reflecting significant social diversity and heterogeneity. In contrast, those in low-quality communities show less social diversity (Figure C).

Appendix

Appendix 0 Result Summary

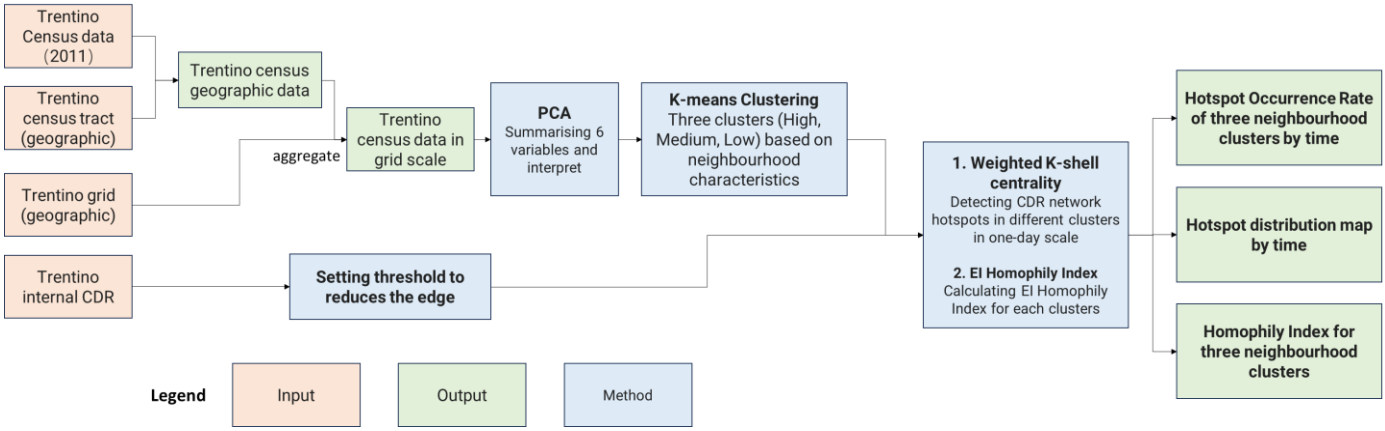




C

EI_Index	Midnight	Morning	Afternoon	Night
High	0.956071	0.974749	0.974649	0.967262
Medium	0.898354	0.909893	0.909051	0.905053
Low	-0.271087	-0.261661	-0.259185	-0.256214

Appendix 1 Research Flow Chart



Appendix 2

$$I_g = I_c\left(\frac{A_{c\cap g}}{A_c}\right)$$

Where: g indicates grid, c indicates census tract. I_c *indicates indicator values of each census tract,* A_c *indicates shape area of each census tract,* $A_{c\cap g}$ *indicates the spatial intersection of census tract and grid.*

Appendix 3 Description of components

PC1: Population density and activity indicators.

PC2: Refreshment level of housing and construction.

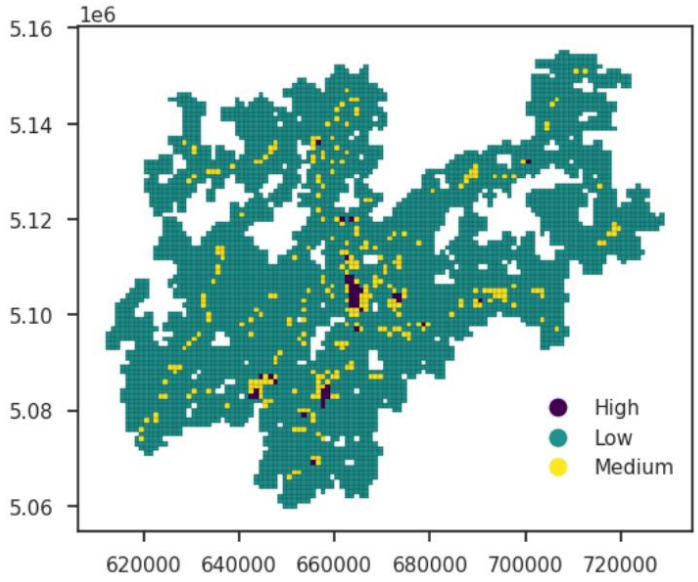
PC3: Housing diversity and level of education.

PC4: Characteristics of the foreign population.

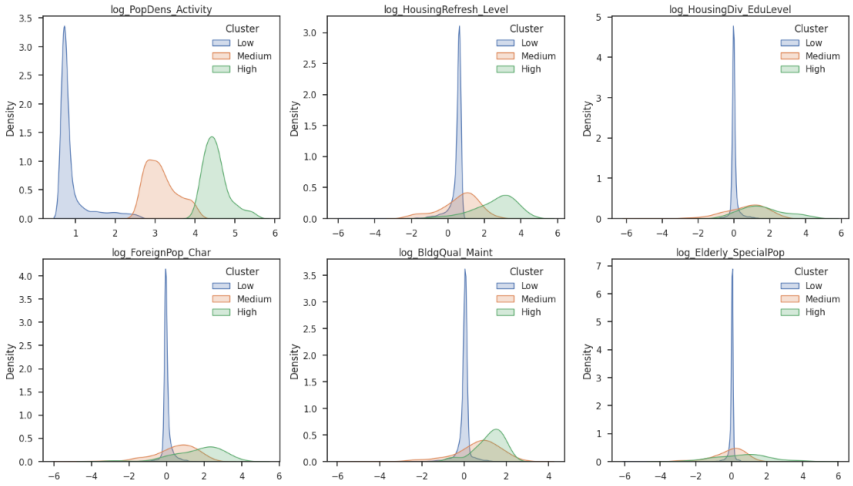
PC5: Building quality and maintenance status.

PC6: Elderly population and special populations (e.g. illiterate).

Appendix 4 Neighbourhood clusters distribution



Appendix 5 Characteristics of Neighbourhood clusters



Appendix 6 Radar Chart of Neighbourhood clusters

Reference

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