



HAL
open science

Combining social network and activity space data for health research: tools and methods

Alexandre Naud, Cédric Sueur, Basile Chaix, Yan Kestens

► To cite this version:

Alexandre Naud, Cédric Sueur, Basile Chaix, Yan Kestens. Combining social network and activity space data for health research: tools and methods. *Health and Place*, 2020, 66, pp.102454 -. 10.1016/j.healthplace.2020.102454 . hal-03494047

HAL Id: hal-03494047

<https://hal.science/hal-03494047>

Submitted on 17 Oct 2022

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution - NonCommercial 4.0 International License

Title

Combining social network and activity space data for health research: Tools and methods

Authors

Naud Alexandre^{1,4} [alexandre.naud@umontreal.ca] (**corresponding author**)

Sueur Cédric^{3,4} [cedric.sueur@iphc.cnrs.fr]

Basile Chaix⁵ [basile.chaix@iplesp.upmc.fr]

Kestens Yan^{1,2} [yan.kestens@umontreal.ca]

Affiliations

¹*Ecole de Sante Publique, Département de médecine sociale et préventive, Université de Montréal, 7101, avenue du Parc, Montréal, Qc, H3N 1X9, Canada*

²*Centre de recherche du Centre hospitalier de l'Université de Montréal, Axe de Recherche Santé des Populations, Pavillon S, 900 Rue Saint-Denis, Montréal, QC H2X 0A9, Canada*

³*Universite de Strasbourg, CNRS, IPHC UMR 7178, 23 Rue du Loess, 67200, Strasbourg, France*

⁴*Institut Universitaire de France, Ministère de l'Enseignement supérieur, de la Recherche et de l'Innovation, 1 rue Descartes, 75231 PARIS CEDEX 05, France*

⁵*Sorbonne Université, INSERM, Institut Pierre Louis d'Épidémiologie et de Santé Publique, Nemesis research team, 6 Boulevard Vincent Auriol, 75646 Paris, France*

1. Background

The last two decades have witnessed a growing interest in the role of social networks in health research (Berkman and Krishna, 2014; Vasylyeva et al., 2016). Methods for collecting and analysing social network data have become increasingly sophisticated (Newman, 2018; Scott and Carrington, 2011) opening new possibilities for understanding how people's health may be influenced by the complex web of social relationships. Similarly, the role of the geospatial environment has been refined, now accounting for daily mobility and exposure to multiple locations, beyond one's residential neighbourhood (Cetateanu and Jones, 2016; Chaix et al., 2013; Cummins et al., 2007; Diez Roux and Mair, 2010; Kwan, 2009; Perchoux et al., 2019; Smith et al., 2019). However, social and spatial contexts are generally studied separately, using tools designed to collect data on social networks (e.g. name generators, RFID sensors) as opposed to those capturing mobility and activity spaces (e.g. GPS recorders, map-based questionnaires). The objective of this paper is to address this issue by presenting a tool and an analytical framework that jointly collect and analyse social networks and activity space data.

1.1. Social networks, activity space and localized face-to-face interactions

Social relationships have been widely studied in the health sciences, yielding substantial evidence that positive aspects of social relationships predict survival (Holt-Lunstad et al., 2010), while lack of social relationships and feelings of loneliness are both risk factors for all-cause mortality (Holt-Lunstad et al., 2015). The quality of social relationships is also linked to a range of disease-related outcomes (Berkman and Krishna, 2014), and is increasingly taken into account in health policies and interventions (Umberson and Karas Montez, 2010).

The complex system of social relations in which people are embedded can be conceptualized as a social network. More generally, a social network refers to a system of relationships between social entities (also called actors). These entities can take different forms, ranging from individuals, groups, to larger entities (e.g. a network of cities), with various characterizations of their relationships (e.g. the flow of people and goods between two cities). In the study of interpersonal relationships, social networks can be used to describe the set of social relationships of a single person, generally known as an egocentric social network (Marin and Wellman, 2011). In the remainder of the article, the term "social network" will refer to this specific usage.

Social network analysis makes it possible to integrate, within a single model, properties of social relationships (e.g. my friend A, whom I see every day, is *supportive* when needed), characteristics of the alters (e.g. A is a

man in his *forties*) and relationships between the alters (e.g. my friends A and B are also *friends with each other*).

One aspect of social networks that remains largely overlooked is the interaction with the geospatial environment in which they are embedded (Adams et al., 2012; Andris, 2016). While the increased use of computer technologies and mobile devices has changed the way people connect with each other (Rainie and Wellman, 2012), in-person face-to-face interactions remain central to our social lives (Hampton et al., 2009). Furthermore, online relationships largely reflect offline relationships (Dunbar et al., 2015; Requena and Ayuso, 2019), and the use of social media does not appear to increase the size of social networks (Dunbar, 2016; Roberts and Dunbar, 2015). Although in-person interactions imply co-occurrence in both time and space with network members, few studies on social networks have considered the geospatial context of face-to-face social interactions.

Consideration of people's mobility and exposure to environmental contexts has gained traction in health research, through the notion of activity space. Activity spaces represent areas in which people move in their everyday lives. They can include the visited locations during a certain period of time (e.g. last week) or at a certain frequency (e.g. at least once a month), or the route travelled between these locations and surrounding areas (Golledge and Stimson, 1996). Thus, activity space provides information about a person's spatial footprint, which facilitates measurement of environmental exposure. In particular, activity space-based research has for example refined our understanding of environmental influence on physical activity, diet, or obesity (Cetateanu and Jones, 2016; Jia et al., 2019; Smith et al., 2019), shifting the focus from the residential neighbourhood to the multiple environments to which a person is exposed.

In comparison with other conceptions of human mobility – such as life paths (Hägerstrand, 1970) or anchor points (Ahas et al., 2009) – some of which are explicitly employed in conjunction with social network data – such as space-time paths (Lee and Kwan, 2011), mobility biography (Axhausen, 2008), or anthropospace (Andris, 2016) – activity space accords particular attention to the visited locations in the course of daily activities. These locations represent high-resolution spatial contexts in which social interactions may take place (e.g. meeting colleagues in the workplace), allowing direct connections between a person's social network and her own activity space. Nevertheless, health research that focuses on activity spaces rarely includes measures of social networks.

1.2. Relevance for health research

Considering the localization of social interactions has significant implications for health research. First, studies that integrate activity space measures to assess environmental impacts on health mostly ignore *the social drivers that explain a person's spatial behaviour* (Kestens et al., 2017). For example, being physically active in one location (e.g. a sports club) may depend on having friends to exercise with, while eating regularly at fast food restaurants may result from a group routine with work colleagues. Various characteristics of social networks have been empirically linked to people's mobility. The time spent on activities depends on the people with whom the activity is conducted (Srinivasan and Bhat, 2008) and increases with the number of people involved (Habib and Carrasco, 2011). The distance travelled also depends on who a person is travelling with (Srinivasan and Bhat, 2008) and long-distance travel is more likely to occur when accompanied (Cho et al., 2011; Phithakkitnukoon et al., 2012). Visited locations and mobility patterns are more similar between connected individuals than between randomly selected individuals (Pelechrinis and Krishnamurthy, 2016; Toole et al., 2015; Wang et al., 2011). Nonetheless, the influence of social networks on activity and travel behaviour remains unclear (Kim et al., 2018).

Second, studies on the role of social networks in health rarely take into account *the broader context in which social relationships are experienced* (Berkman and Krishna, 2014). Social interactions frequently occur outside the home or workplace (Picornell et al., 2015) in a range of locations that are important to social life within communities (Oldenburg, 1999). Public space is seen as a social space in urban design (Gehl, 2011), while commercial spaces, such as cafes, restaurants and bars, have a fundamental social function by allowing people to meet and exchange support and companionship (Rosenbaum, 2006). In addition, the way the environment is constructed and perceived plays a role in socialization. The presence and amount of vegetation in common outdoor public spaces (Coley et al., 1997; Kweon et al., 1998), neighbourhood walkability (Leyden, 2003) and urban density have been positively related to social interactions, while environments that inspire fear of crime (e.g. dark alleys, abandoned infrastructures) discourage people from interacting with each other (Palmer et al., 2005).

Third, studying the geolocation of social interactions allows us to examine *the collective patterns in which individuals interact in space*. Subgroups of individuals sharing similar social attributes may interact in common places. In the Netherlands, people with a higher level of education are more likely to interact at work, while those with higher incomes appear to interact more in outdoor public spaces (van den Berg et al., 2010). In deprived neighbourhoods in the UK, people who are unemployed, retired, in poor health or with a child at home are more likely to have social interactions in third places (i.e. outside the home and workplace) (Hickman, 2013). In the United States, fast food restaurants are important locations in which older people

build and conduct their social lives (Cheang, 2002). In Amsterdam, local pubs may serve as an “inclusive space” by allowing interactions between different populations in neighbourhoods undergoing gentrification (Ernst and Doucet, 2014). Understanding these differences can help identify places that are socially relevant to vulnerable populations and understand the impact of urban transformation on social cohesion among different populations.

1.3. Existing methods for localizing social interactions

Modern large-scale communication databases (e.g. mobile phone records, Foursquare) have provided substantial information on the interrelations between social networks and geospatial environments (e.g. (Crandall et al., 2010; Hristova et al., 2016; Pelechrinis and Krishnamurthy, 2016; Phithakkitnukoon et al., 2012; Toole et al., 2015)). These databases provide solid information on the organisation and dynamics of people's social and spatial behaviour, allowing the characterisation of large social network structures and detailed mobility patterns. They provide, however, no direct information on localized face-to-face interactions. While information on co-presence has been used to infer social contacts (e.g. (Crandall et al., 2010)), it remains a proxy to face-to-face social interaction. These secondary databases also limit possibilities for collecting additional individual-level information that may be useful for health research. Finally, some populations that are less likely to use the technologies may be under-represented.

A second approach is to measure localized social interactions using activity diaries—a survey in the form of a logbook in which individuals report and document all activities performed during the day (Stopher, 1992). This method is mainly used in transportation research to collect data on travel behaviour. People with whom activities are undertaken can also be collected, providing measures of geolocalised face-to-face social interactions (e.g. (Farber et al., 2014; van den Berg et al., 2010)). Measures of social networks can further be collected from daily social interactions (e.g. (Doherty et al., 2004; Lee and Kwan, 2011)) in an approach similar to a contact diary (i.e. which people are seen during each identified activity) (Fu, 2005). Since data are collected over time, the strength of this method is that it can assess detailed temporal information such as the length and time of day when face-to-face social interactions occurred. Nevertheless, the data are collected for short periods of time, between one and several days, resulting in only a partial representation of a person's activity space and social network, constrained by the duration of the survey.

A third approach to collecting social and spatial information is to use recall-based questionnaires. A strength of this approach is that the reported information does not need to be restricted to recent, within-day, events. Social network information is often collected in this way by asking respondents to name the people

with whom they are in contact in some way (i.e. the people with whom the respondent likes to socialize). This approach, called a name generator, can be easily adapted to collect localized face-to-face interactions. One application is the study by Carrasco and colleagues (2008). Social relationships are first collected by a name generator, and the locations of social episodes, defined as "visiting, receiving visitors or meeting in restaurants, pubs or similar places" (Carrasco et al., 2008, p.12) are then measured for a subset of close and frequent relationships. Visited locations can also be recalled independently. This was applied in the study by Mason and colleagues (2010) on adolescent substance use. Using a name generator and an activity space questionnaire, respondents identify up to five close relationships, and document all visited locations in their weekly routine. Social networks and activity spaces are then linked a posteriori by asking "who in your network is with you at each location?" Compared to the approach used by Carrasco and colleagues (2008), this approach provides a broader assessment of activity spaces, since visited locations are not limited to social episodes. However, social networks are likewise limited to a few close relationships, and the assessment of weekly routine locations limits the scope of measured activity spaces.

The main drawback of existing questionnaires and diaries is that they generally provide selected assessments of respondents' social networks and activity spaces. While specific dimensions of social and spatial contexts may be relevant to specific health issues, we argue that assessing a broader spectrum of social relationships and visited locations provides a more comprehensive picture that is useful for health research. Second, several data collection tools have been designed for a pen-and-paper format, which increases the burden of the interview process and the transfer of collected information to digital databases, which is a challenge, given the complexity of the data collected. In addition, pen-and-paper surveys tend to contain more errors than computer-assisted surveys (Caeyers et al., 2010).

The following section presents a novel interactive questionnaire that combines a name generator with an existing map-based questionnaire, permitting the joint collection of detailed information on social networks and activity spaces.

2. VERITAS-Social : A socio-spatial questionnaire

2.1. The questionnaire

VERITAS-Social is an adaptation of VERITAS (Visualization and Evaluation of Route Itineraries, Travel destinations, and Activity Spaces), a map-based questionnaire allowing respondents to easily locate places, routes, and other areas of interest on an interactive map, either as points, lines or polygons (Chaix et al., 2012). For each reported element, additional information can be reported, such as frequency of visits, level of place attachment, transport modes used, etc. This questionnaire has been used in a variety of settings to study various populations and health outcomes for which daily mobility and multiple exposures to the built environment can play a role (Hinckson et al., 2014; Perchoux et al., 2015; Schmidt et al., 2018; Stewart et al., 2015). Because the collected data includes geographic coordinates, they can be easily linked to other spatial databases describing the geospatial environment.

In its original version, VERITAS respondents were asked to locate a list of predefined activities on a map (e.g. do you go to a park at least once a month, if yes, please locate). We added to this module a name generator to assess respondents' interactions with other people at that location. Name generators are commonly used to assess social networks by asking respondents to list their social relationships according to one or more criteria, such as the type of relationships (e.g. listing friends) or behavioural exchange (e.g. listing who provides support) (Marsden, 2005). The composition of social networks measured with a name generator will depend on the specific prompt used to obtain network members (Milardo, 1992), although there are similarities between networks measured using different ones (Shakya et al., 2017). In our questionnaire, respondents are asked whether the reported activities are carried out alone or with someone else. When selecting the latter, they may identify one or more individuals, or groups of individuals (e.g. the community centre choir). Due to the interactive format of the questionnaire, respondents can identify new or previously reported network members when documenting an additional location, thus reducing redundant information collection. For each person and group added, follow-up questions can provide additional information, such as role relationships (e.g. friends, family), frequency of interaction, people's socio-demographic attributes, or number of people in groups (Figure 1). Compared to other name generators, the particularity of our approach is that relationships are identified based on visited locations, which means that reported social networks are initially prompted by in-person interactions occurring in people's activity spaces.

Once all the visited locations have been mapped and the corresponding names have been generated, the respondents review the complete list of documented people. To more accurately assess the nature of the relationships, respondents can characterise relational properties, identifying those who provide support and

companionship. During this phase, other network members can be added, thus extending the social network description beyond people regularly met in one's activity space. In health research, considering close relationships with people who are not regularly seen in person may be particularly important for analysing social support (e.g. a child living away from home who is usually contacted by telephone). Finally, the respondent is presented with a visual representation of reported individuals and group, on which she can draw lines to indicate interpersonal relationships between individuals (e.g. friends A and B know each other), and whether individuals are also part of a reported group (e.g. my sister is part of the community centre choir).

The questionnaire was built as a secure online application by Polygon Research Inc. It integrates the Google Application Programming Interface (API) to display maps on which the respondent can report spatial information. It also allows respondents to search for addresses or location names inside the Google database. The questionnaire can either be administered or self-administered if respondents have some level of familiarity with the use of the online user interface.



Figure 1: Diagram of the questionnaire flow chart. The left side represents the original VERITAS interface where the respondent can report and comment on the location of the activities. The right side represents the name generator used to assess the respondent's social network based on geolocalized activities.

2.2. Validity and reliability of VERITAS-Social

Information collected through VERITAS-Social relies on respondents' ability to self-report visited locations and alters. A validation study comparing 7-day GPS tracking and reported visited locations through VERITAS conducted with 234 participants showed 85.5% of GPS points were located within 500 m of a reported VERITAS location (Kestens et al., 2018). Test-retest reliability of the original VERITAS questionnaire was also conducted with 31 adults over a two-week interval and reported an agreement for 86.5% of collected locations between the test and the retest (Shareck, Kestens, & Gauvin, 2013).

When assessing the validity of social network measures, name generators tend to provide more simplified networks than wearable proximity sensors, as the former tend to under-report interactions of short duration (Mastrandrea et al., 2015; Smieszek et al., 2014). Friendship surveys also provide less alters compared to Facebook data (Mastrandrea et al., 2015), likely because online contacts are easier to document, and include a wider range of relationships (e.g. family, acquaintance, co-worker). In a review of the reliability of name generators, the average test-retest agreement of reported alters ranged between 78% and 92% (Brewer, 2000). People were also better able to recall strong, rather than weak, emotional ties (Brewer, 2000; Brewer and Webster, 2000). In conclusion, recall-based self-reported methods seem to over-represent contacts of longer cumulative duration and closer emotional ties.

The reported characteristics of alters, which constitute most of the social network data, may also raise validity issues. Previous studies have shown that the respondent can provide several of these characteristics with reasonable accuracy (Marsden, 1990). Reported information is more valid for close relationships than for distant ones, and people are relatively good at reporting what they can observe directly about their alters (Marsden 2000). Caution should, however, be exercised in the choice of data to be collected, as the respondent may lack some information on her alters (e.g. political orientation, health status). Information that is directly experienced by the respondent (e.g. length of relationships) is likely to be more valid.

Structure of collected data

The data collected with VERITAS-Social covers social network information, activity space information and socio-spatial relations between alters and visited locations. The term "alters" here refers both to people declared individually (e.g. the neighbour) or as groups (e.g. the choir members).

Properties of social networks can be described using social network analysis (Scott and Carrington, 2011), while indicators of spatial behaviour can be derived from activity space data (Chaix et al., 2012). Such

individual-level descriptors can then be linked to health outcomes. Activity space data can be further integrated into a geographic information system, and linked to environmental conditions to which the respondent is exposed. The novelty of VERITAS-Social is that social network data and activity space information are directly linked. This means that social relationships can be geo-referenced in accordance with the locations of social interactions, and visited locations can be characterized by the face-to-face interactions they host. In the next section, we discuss how these complex relational data can be effectively analysed using network theory.

3. Investigating linked socio-spatial data using network theory

Network theory is used to describe the relationships between real world entities. By providing a comprehensive set of mathematical and computational techniques mostly founded on graph theory, it captures properties that emerge from the pattern of connections between its constitutive elements (see (Newman, 2018) for comprehensive introduction on network science).

Network theory has previously been used to analyse comparable socio-spatial data obtained from large-scale communication databases (e.g. (Hristova et al., 2016; Pelechrinis and Krishnamurthy, 2016)). The difference is that these studies focus on sociocentric social networks (i.e. a set of interconnected people), and that socio-spatial relationships define the locations visited by people. As a result, they do not assess face-to-face social interactions from an egocentric perspective but reflect the extent to which people visit common locations.

In its simplest form, a network is composed of a set of elements, called *nodes*, connected to each other by *edges*. Many types of systems can be described as networks, such as airport-to-airport flights (Guimera and Amaral, 2005) or scientific collaborations (Barabasi et al., 2002). Modern social network analysis is mainly based on network theory (Scott and Carrington, 2011), although it is not simply an application of the latter, as its roots go back a long way in sociological research (see Freeman (2004) for an historical review). The information collected with VERITAS-Social can also be represented in the form of a network, with the particularity that the nodes are made up of two distinct sets of elements, namely alters and visited locations.

The relationships between visited locations and alters depend on “with whom activities are conducted.” This constitutes a *bipartite network* composed of two disjoint sets of nodes with edges defined between the nodes of the different sets only (Latapy et al., 2008). This type of network captures the patterns that characterize a person’s interactions with the members of her social network in her activity space (see Figure

2). The limitation of bipartite networks is that they do not include connections between alters or between locations. Adding these relationships to the bipartite network results in a *system of interconnected networks* consisting of two sub-networks with connections within and between them (Donges et al., 2011). The two sub-networks — the social network and the activity space represented as a spatial network — are linked by face-to-face interactions (i.e. the edges previously defined in the bipartite network) (see Figure 2). Relationships between alters (i.e. within the social network) are directly identified when answering the "who knows whom" question. While links between locations are not directly assessed in VERITAS-Social, they can be characterized in different ways, for example using the distance between locations — close locations being more strongly linked than distant ones. Other types of links could be considered, such as location of origin when reaching a given destination — the relationships could in that case be a function of the frequency of travel between locations. In both the bipartite and interconnected models, the respondent is not a node within her network. Since the respondent is, by default, connected to all alters and all locations, this information is irrelevant. Furthermore, the edges between the respondent and visited locations are not comparable to those between alters and visited locations, as the former represent *visited locations by the respondent* and the latter represent *activities conducted with alters*.

Network theory provides useful analytical tools for studying the patterns of connection that occur within and between a person's social network and her activity space. A range of measures and algorithms have been developed to describe networks, from local node characteristics to global network structures. In the following section, we present some key measures we consider relevant to the characterization of these socio-spatial relationships. A detailed discussion of network measures and algorithms is beyond the scope of this paper; we refer the reader to (Latapy et al., 2008) for a review of basic bipartite network measures, and (Donges et al., 2011) for an introduction to interconnected networks. We also refer the reader to (Kivelä et al., 2014), who review the more general models of multilayer networks, of which bipartite and interconnected networks are specific instances. Networks can also be visualized in a two-dimensional space, which is an effective way of exploring relational data and communicating results. The position, size, shape and colour of nodes and edges can reflect various dimensions of the system. The use of visual representations allows multiple pieces of information to be communicated simultaneously, providing a comprehensive and multivariate view of such socio-spatial relationships (Krempel et al., 2011). The following section presents a case study illustrating the application of network analysis to joint social network and activity space data.

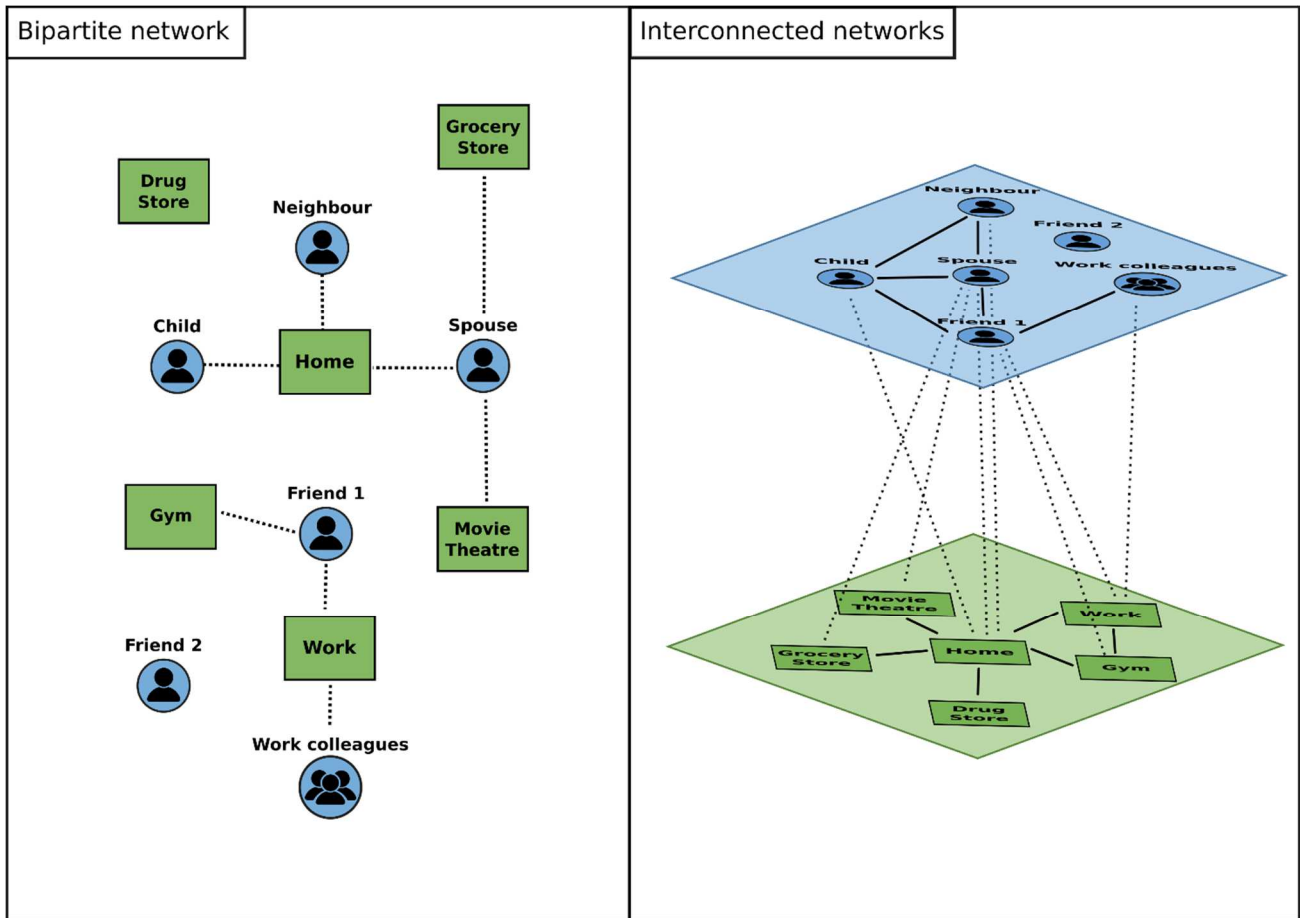


Figure 2: Hypothetical examples of a bipartite network and a system of interconnected networks modelling the relationships between social networks and activity spaces. Alters are represented by blue circles. Individuals and groups are distinguished by the number of people represented in the circle. Places are represented by green rectangles. In bipartite networks, socio-spatial relationships are represented as dotted lines. These relations identify who is seen in which location. It shows, for example, that Child is only seen at Home, while Friend 1 is seen both at the Gym and at Work. It also shows that the Pharmacy is disconnected from the rest of the network, which means that the respondent does not see anyone from her network at that location. In interconnected networks, the relationships between people and visited locations are added: the social network (blue circles) is connected to the spatial network (green polygons) by who is seen at a given location (dotted lines). The edges between alters represent "who knows whom." For example, Neighbour knows Child and Spouse. In comparison, Friend 2 is not connected, meaning he does not know any other alter. The edges between locations could represent different relationships (e.g. distance), but these are not defined by the respondent in VERITAS-Social. The respondent is not represented in either the bipartite or interconnected network, knowing that by definition, she is connected both to all people (she knows everyone in her network) and to all locations (she visits all locations). The length of the lines is not informative in these examples.

4. Case study

4.1. Sample source

Source data for the case study comes from the CURHA (Contrasted Urban settings for Healthy Aging) study, an international research project on healthy aging involving two samples of populations living in Canada and Luxembourg (see Kestens and colleagues (2016) for more information on the CURHA project). We used data from the Canadian study sample composed of 183 people aged from 80 to 95 years living in the community in different regions of the province of Quebec. To illustrate the information captured by VERITAS-Social and the type of measures network analysis can provide, we extracted data from two participants—an 83-year-old woman (participant A) and a 90-year-old man (participant B) living in urban and rural areas respectively.

4.2. Network analysis

We computed the bipartite networks of participants A and B. People and locations are represented by single nodes. Groups are represented as \sqrt{n} nodes, where n is the number of people in the group who were not also identified individually (e.g. my friend is also in the volunteer group). We used the square root of the group size to minimize the influence of large groups on the total size of the network (see further details in section S4 of supplementary materials).

We computed *size*, *density*, *degree* and *community structures*. The *size* of the network refers to the number of nodes, in this case, both the number of alters and locations. The *density* is the ratio between the number of edges and the maximum possible number of edges in the network and provides a measure of the overall connectivity of the network. This ranges from 0 to 1, with 0 meaning that no alters are seen at any locations, and 1 meaning that all alters are seen at every location. The *degree* of a node is defined by the number of connections it has to other nodes. In our case, the degree of an alter is the number of locations where he is seen, and the degree of a location is the number of alters seen there. We further separated the bipartite networks into *communities*, namely groups of nodes that have a greater likelihood of being connected to each other than to the rest of the network. We have identified communities that do not overlap (i.e. each node belongs to a single community), including both alters and places. These communities reflect alters commonly observed in shared places. Communities were calculated using the Liu and Murrata (2009) algorithm. To further evaluate the position of nodes according to identified communities, we calculated the *within-module degree*, a measure of the quality of connection of a node to other nodes in its own community, and *the participation index*, which indicates the extent to which a node is connected to other communities in the network. The first index is a z-score of the relation between a node degree and the community average degree, the second index takes a value of 0 if all its connections are within its own

community, and tends towards 1 if its connections are evenly distributed in all communities of the network (Guimerà and Amaral, 2005).

We computed the interconnected networks by adding the relationships between the alters, defined by "who knows whom." Interpersonal relationships were only defined between individually reported people. Although people generated from a same group could be considered all related to each other, we had no information on inter-group relationships (e.g., do people in group A and B know each other?) or between groups and individually identified people (e.g., does the spouse know people in group A?).

We then calculated the *cross-clustering coefficient*. This measure evaluates, for any node in a given sub-network, the proportion of its neighbours (i.e. the nodes directly connected to it) in the other sub-network that are directly connected to each other (Donges et al., 2011). Therefore, the cross-clustering coefficient for a location assesses the extent to which people seen at that location know each other. The cross-clustering coefficient was not calculated for the alters in this case study since relationships between locations were not defined.

We provide a detailed description of these measures and algorithms in section S1 of the supplementary materials. All network analyses were performed in R 3.5.1 (R Core Team, 2013) using igraph 1.2.1. (Csardi and Nepusz, 2006). Visual representations of the bipartite networks were generated using Gephi 0.9.2. (Bastian et al., 2009). Characteristics of alters and locations were also measured – see Section S3 of the supplementary materials for a detailed description of these variables.

4.3. Results

The map of the reported visited locations and the visual representations of the bipartite networks are shown in Figures 3 and 4, respectively. Node-level measurements for the bipartite and interconnected networks are presented in Tables S1 and S2 in Section S2 of the supplementary materials. The characteristics of the alters and locations are presented in Tables S3 to S6 in Section S3 of the supplementary material.

Participant A's bipartite network consists of 12 alters and 12 locations. Among alters, 4 were reported individually (A1 to A4) and 8 were generated from two groups (A5 and A6; A7 to A12). Participant B's network is larger, with 19 alters and 11 visited locations—there are no groups in this network. Both networks have a relatively low density, with 13% and 16% of the maximum possible number of edges for participants A and B, respectively. The degree distribution follows a similar pattern in both networks, consisting mainly of

low degree nodes with a few high degree nodes. These degree distributions are partly explained by the observed community structures, which consist of multiple star-shaped communities, characterized by one high degree node connected to several low degree nodes. This is indicative of a person with whom multiple activities are carried out or a location where several alters are seen.

An in-depth analysis that takes into account the attributes of the nodes permits a better understanding of these relational patterns. Participant A's activity space is primarily concentrated in her residential neighbourhood (see Figure 3), where she walks to many locations. It includes the church (L9) where she sees most of her alters, in her volunteer group and choir. All these nodes form the largest community in its network (purple). In her residential neighbourhood, we find her home (L6), the residence of two alters (L7, L8) where she sees four people (A1 to A4), as well as other functional locations (L10 to L12) that she visits alone. She visits all the locations outside her residential neighbourhood (L1 to L5) with her child (A1), forming the second largest community in her network (green). She reported she is driven there, suggesting that A1 accompanies the participant for these functional activities (i.e. shopping and medical appointments).

Participant B's activity space is more dispersed, with a median distance of 11.39 km between home and visited locations, compared to 1.1 km for Participant A. This is probably linked to the fact that Participant B lives in a rural area while Participant A lives in a peri-urban area. Only one location—the residence of an alter (L14) where family visits take place (A13 and A14)—is within walking distance. These family members are also seen at his home (L13), all of these nodes forming a community (orange). The three other communities are centred on the spouse (A19; green), the church (L23; purple) and a restaurant (L15; blue), which are also the most connected nodes in the entire network. In addition, 89% of face-to-face interactions are linked to the church and the restaurant. It is interesting to note that the spouse is the most intermediate node in the network (participation index = 0.68), having connections to all four communities. The spouse likely drives the participant to 81% of the visited locations, which suggests the importance of this node in the network.

There are five additional edges in Participant A's interconnected networks. The cross-clustering coefficient was only calculated for the main residence (L6)—this is the only location where the participant sees multiple people reported individually (i.e., A1 to A3). This location has a coefficient of 0.67, which means that there is 67% of the maximum number of interpersonal connections between the people seen there (i.e. who knows whom). There are 98 additional edges in Participant B's interconnected networks. Most locations have a value of 1 for the cross-clustering coefficient. Only the restaurant (L15) has an intermediate value, with a

coefficient of 0.4, which means that there is 40% of the maximum number of interpersonal connections between the people seen there.

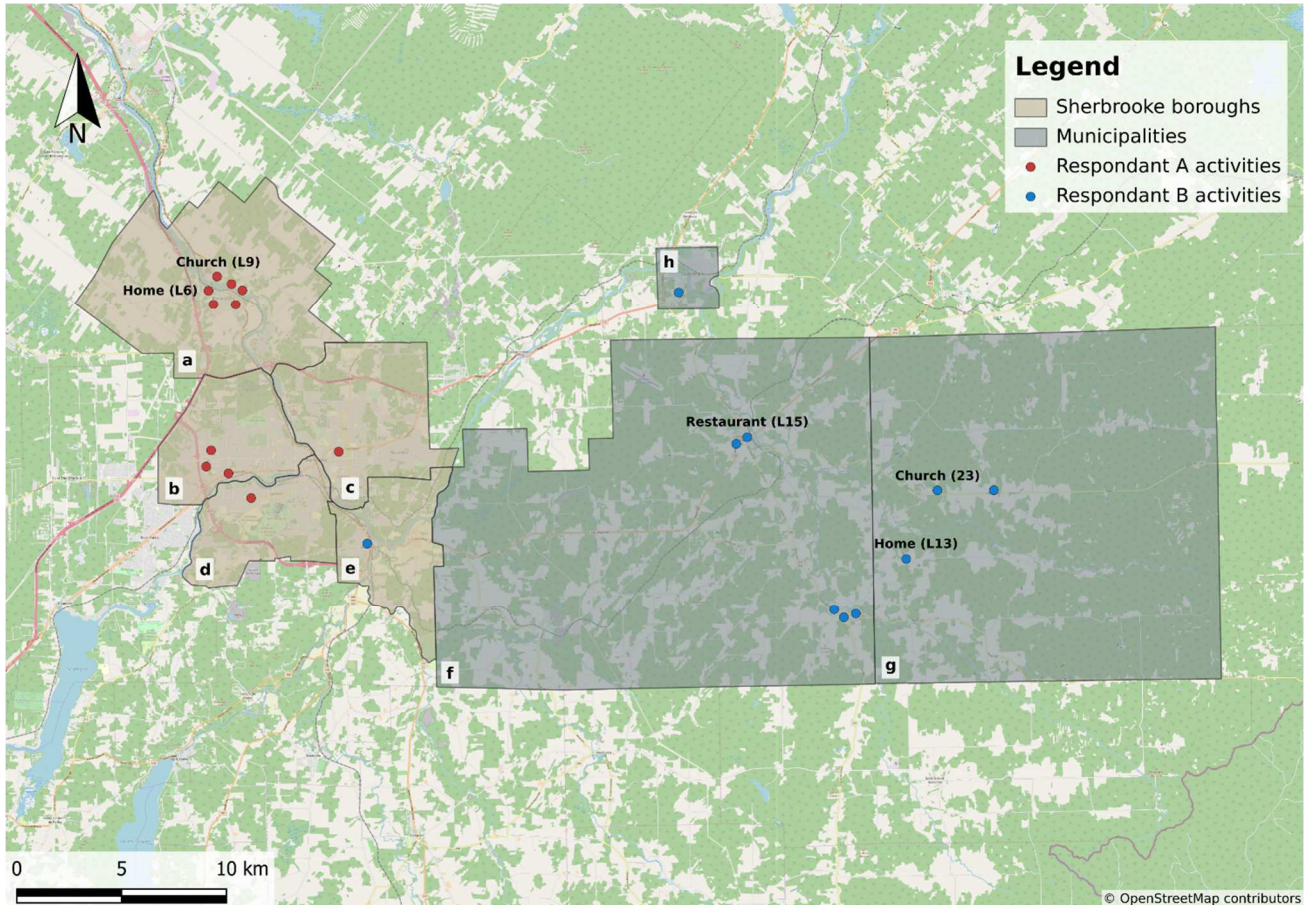


Figure 3: Spatial distribution of participants A and B visited locations. The polygons represent Sherbrooke boroughs (a = Brompton–Rock Forest–Saint-Élie–Deauville, b = Jacques-Cartier, c = Fleurimont, d= Mont-Bellevue, e = Lennoxville) and Quebec municipalities (f = Cookshire-Eaton, g = Newport, h = East Angus). The primary residence has been removed and geographical coordinates of displayed locations have been randomly modified by a factor of 0.02 to ensure confidentiality. Overlapping locations were moved further apart manually to improve visualization. The different areas contain the following locations: (a contains L6 to L12), (b contains L2, L4, and L5), (c contains L3), (d contains L1), (e contains L17), (f contains L18, L20, L21, L22 and L25), (g contains L16, L23 and L24), (h contains L19). The map is projected in WGS 84 / Pseudo-Mercator at 1:325 000 scale. Basemap layer is from the OpenStreetMap database (OpenStreetMap Contributors, 2012).

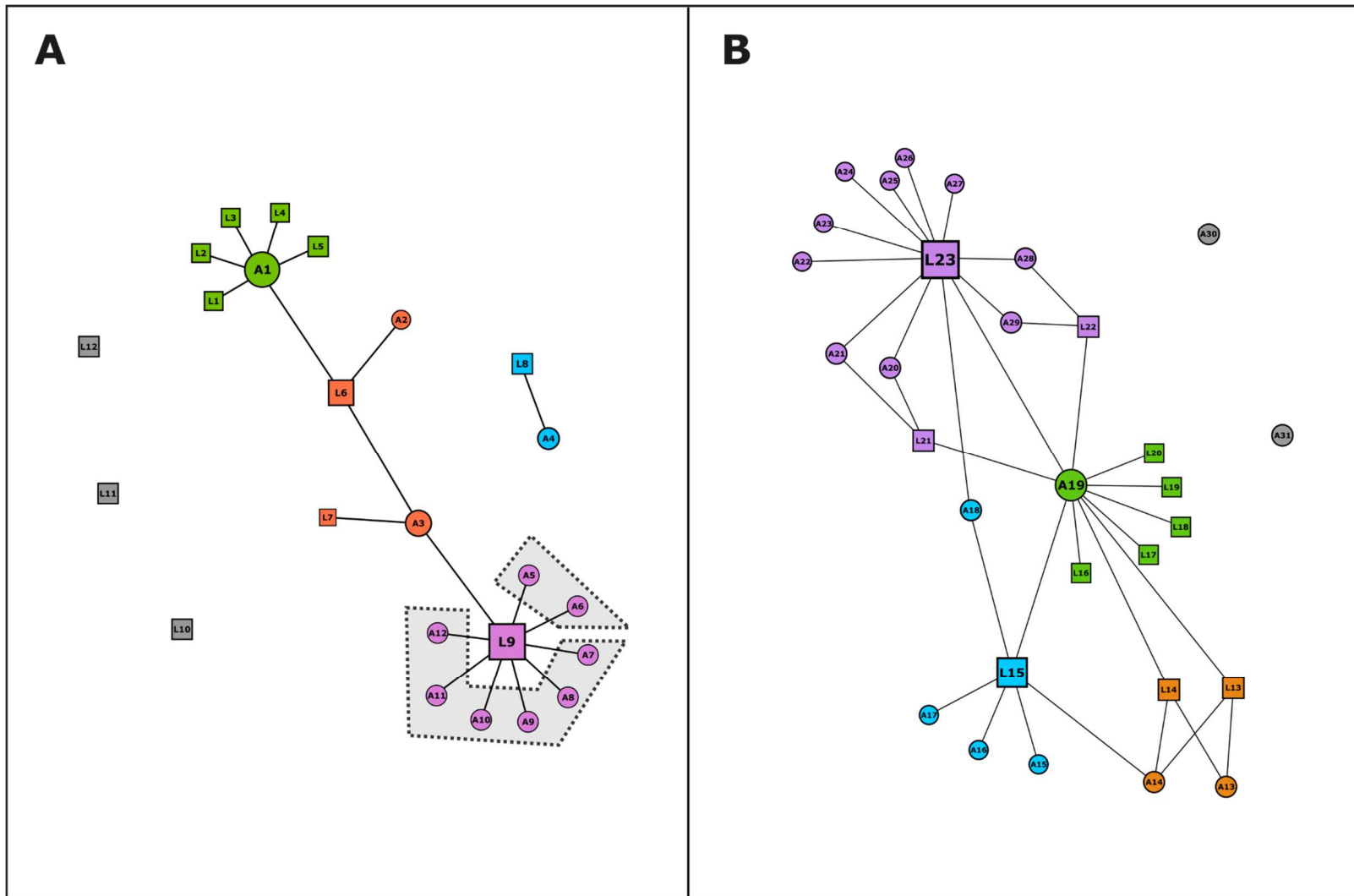


Figure 1: Visual representation of participants A and B's bipartite networks. Locations (L_x) are represented as squares and alters (A_x) as circles. Light grey polygons surround alters generated from groups. Edges represent "with whom activities are conducted." For example, participant A sees three alters (i.e. A1 to A3) in location L6. The colours of the nodes represent the communities to which they belong. The size of the nodes is proportional to their within-module degree. A default minimal size was attributed to unconnected nodes, although their within-module degree is undefined. Node sizes therefore emphasize their connectivity with their own community. For example, L9 is the most connected node in its community, and therefore the largest. The position of each node in a two-dimensional space was calculated with the Force Atlas layout algorithm. Both the length and width of the edges are derived from the layout algorithm and do not represent any attribute.

5. Discussion

VERITAS-Social is a novel online tool for collecting data on people's activity spaces and social networks. VERITAS-Social integrates a map-based questionnaire with a name generator, permitting in-depth evaluation of socio-spatial information in terms of the number and type of visited locations and people met in person. The particularity of this tool is that social and spatial data are further linked by the location of face-to-face social interactions. It therefore offers a means of assessing how spatial and social environments interact at the individual level, which can improve our understanding of how spatial and social contexts influence health.

This proposed online application offers several benefits, given the inherent complexity of the data collected. The visited locations can be directly identified on an interactive map while the social networks are progressively documented in a recursive process. The data collected can be easily transferred into formats suitable for geospatial and social network analysis. The questionnaire can also be easily adapted to a variety of research topics, and can be used in combination with other instruments such as GPS devices and smartphone-based surveys (e.g., ecological momentary assessment of localized social interactions) to arrive at more accurate estimates of people's activity spaces and social networks. These data can also easily be connected to other geospatial information, to improve contextual exposure estimates.

One limitation of the current VERITAS-Social is that its validity and reliability are evaluated on the basis of studies conducted on each component separately. Validity studies of name generators suggest that typical close social relationships are possibly over-represented. The activity space module may also be less suitable for episodic destinations than for habitual destinations. Further investigation on the validity and reliability of the combined use of spatial and social data collection is needed. In the version of VERITAS-Social that was used in the CURHA study, there was no assessment of socialization through modern communication technologies, because the main goal was to understand the spatialization of social interactions. However, other more recent deployments have also included questions on phone, online, or text-message interactions (e.g. the COHESION Study (www.cohesionstudy.ca)). In a COVID-19 context in which numerous interactions have gone online, VERITAS-Social could possibly include questions aimed at discriminating between online interactions that replace real-world social life from those that maintain pre-existing geographically distant relationships (Liu et al., 2016).

One challenge with VERITAS-Social is the complexity of the data collected. We have shown that network theory provides a useful framework for studying these socio-spatial data, providing mathematical and computational methods for describing relationships between and within social relationships and visited locations. These systems can be modelled as multilayered networks, either bipartite networks or systems of interconnected networks. Bipartite networks remain easier to analyze and interpret because they include only one type of edge. In interconnected networks, three types of edges can be defined, which means that every node can be connected to all other nodes of the system. Since network properties are based on connectivity patterns, the interpretation of interconnected network measures becomes more complex. In addition, since relationships between locations can be defined in various ways, so can the interpretation of their properties. Overall, we believe that both bipartite and interconnected networks are complementary as they provide information on different aspects of these systems.

The case analysis using data from the CURHA study illustrated the possibilities of modelling VERITAS-Social data as a complex network. It revealed, among other things, the presence of star-shaped communities composed of multiple low-degree nodes connected to a central high-degree node. It showed how certain people appeared to play a particularly important role in these seniors' mobility, and how certain locations act as key settings for social interactions. These high-degree nodes can potentially influence exposure to health-relevant resources (e.g. a location where the senior experiences companionship, or a close relationship who accompanies the senior to her medical appointment) which raises questions about the capacity to reorganize the network following the potential loss of one of these central nodes.

By collecting comprehensive data on people's social relationships in combination with localized information on their regular activities, VERITAS-Social combined with network theory offers new possibilities for understanding the complex interaction between health-relevant social and spatial exposures. As the case study shows, exploring the relationships between social networks and activity spaces reveals patterns that could not be observed by studying these contextual datasets in isolation. By directly examining the links between social and spatial contexts, we may obtain a better understanding of the processes by which environments influence health.

6. Bibliography

- Adams, J., Faust, K., Lovasi, G.S., 2012. Capturing context: Integrating spatial and social network analyses. *Soc. Netw.* 34. <https://doi.org/10.1016/j.socnet.2011.10.007>
- Ahas, R., Silm, S., Saluveer, E., Järv, O., 2009. Modelling home and work locations of populations using passive mobile positioning data, in: Gartner, G., Rehl, K. (Eds.), *Location Based Services and TeleCartography II, Lecture Notes in Geoinformation and Cartography*. Springer, Berlin, Heidelberg, pp. 301–315.
- Andris, C., 2016. Integrating social network data into GISystems. *Int. J. Geogr. Inf. Sci.* 30, 2009–2031. <https://doi.org/10.1080/13658816.2016.1153103>
- Axhausen, K.W., 2008. Social Networks, Mobility Biographies, and Travel: Survey Challenges. *Environ. Plan. B Plan. Des.* 35, 981–996. <https://doi.org/10.1068/b3316t>
- Barabasi, A.L., Jeong, H., Neda, Z., Ravasz, E., Schubert, A., Vicsek, T., 2002. Evolution of the social network of scientific collaborations. *Phys. Stat. Mech. Its Appl.* 311, 590–614. [https://doi.org/10.1016/S0378-4371\(02\)00736-7](https://doi.org/10.1016/S0378-4371(02)00736-7)
- Bastian, M., Heymann, S., Jacomy, M., 2009. Gephi: an open source software for exploring and manipulating networks. *Proc. Third Int. ICWSM Conf.* 8, 361–362. <https://doi.org/10.13140/2.1.1341.1520>
- Berkman, L.F., Krishna, A., 2014. Social network epidemiology, in: Berkman, L.F., Kawachi, I., Glymour, M. (Eds.), *Social Epidemiology*. Oxford University Press, p. 234.
- Brewer, D.D., 2000. Forgetting in the recall-based elicitation of personal and social networks. *Soc. Netw.* 22, 29–43. [https://doi.org/10.1016/S0378-8733\(99\)00017-9](https://doi.org/10.1016/S0378-8733(99)00017-9)
- Brewer, D.D., Webster, C.M., 2000. Forgetting of friends and its effects on measuring friendship networks. *Soc. Netw.* 21, 361–373. [https://doi.org/10.1016/S0378-8733\(99\)00018-0](https://doi.org/10.1016/S0378-8733(99)00018-0)
- Caeyers, B., Chalmers, N., De Weerd, J., 2010. A Comparison of CAPI and PAPI through a Randomized Field Experiment. Available SSRN. <http://dx.doi.org/10.2139/ssrn.1756224>
- Carrasco, J.A., Hogan, B., Wellman, B., Miller, E.J., 2008. Collecting Social Network Data to Study Social Activity-Travel Behavior: An Egocentric Approach. *Environ. Plan. B Plan. Des.* 35, 961–980. <https://doi.org/10.1068/b3317t>
- Cetateanu, A., Jones, A., 2016. How can GPS technology help us better understand exposure to the food environment? A systematic review. *SSM - Popul. Health* 2, 196–205. <https://doi.org/10.1016/j.ssmph.2016.04.001>
- Chaix, B., Kestens, Y., Perchoux, C., Karusisi, N., Merlo, J., Labadi, K., 2012. An interactive mapping tool to assess individual mobility patterns in neighborhood studies. *Am. J. Prev. Med.* 43, 440–50. <https://doi.org/10.1016/j.amepre.2012.06.026>

- Chaix, B., Méline, J., Duncan, S., Jardinier, L., Perchoux, C., Vallée, J., Merrien, C., Karusisi, N., Lewin, A., Brondeel, R., Kestens, Y., 2013. Neighborhood environments, mobility, and health: Towards a new generation of studies in environmental health research. *Rev. Epidémiologie Santé Publique, Déterminants sociaux de la santé : les apports de la recherche en santé publique* 61, S139–S145. <https://doi.org/10.1016/j.respe.2013.05.017>
- Cheang, M., 2002. Older adults' frequent visits to a fast-food restaurant: Nonobligatory social interaction and the significance of play in a "third place." *J. Aging Stud.* 16, 303–321. [https://doi.org/10.1016/S0890-4065\(02\)00052-X](https://doi.org/10.1016/S0890-4065(02)00052-X)
- Cho, E., Myers, S.A., Leskovec, J., 2011. Friendship and Mobility: User Movement in Location-based Social Networks, in: *Proceedings of the 17th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, KDD '11.* ACM, New York, NY, USA, pp. 1082–1090. <https://doi.org/10.1145/2020408.2020579>
- Coley, R.L., Sullivan, W.C., Kuo, F.E., 1997. Where Does Community Grow?: The Social Context Created by Nature in Urban Public Housing. *Environ. Behav.* 29, 468–494. <https://doi.org/10.1177/001391659702900402>
- Crandall, D.J., Backstrom, L., Cosley, D., Suri, S., Huttenlocher, D., Kleinberg, J., 2010. Inferring social ties from geographic coincidences. *Proc. Natl. Acad. Sci.* 107, 22436–22441. <https://doi.org/10.1073/pnas.1006155107>
- Csardi, G., Nepusz, T., 2006. The igraph software package for complex network research. *InterJournal Complex Systems*, 1695–1703.
- Cummins, S., Curtis, S., Diez-Roux, A.V., Macintyre, S., 2007. Understanding and representing 'place' in health research: A relational approach. *Soc. Sci. Med., Placing Health in Context* 65, 1825–1838. <https://doi.org/10.1016/j.socscimed.2007.05.036>
- Diez Roux, A.V., Mair, C., 2010. Neighborhoods and health. *Ann. N. Y. Acad. Sci.* 1186, 125–145. <https://doi.org/10.1111/j.1749-6632.2009.05333.x>
- Doherty, S.T., Nemeth, E., Roorda, M., Miller, E.J., 2004. Computerized household activity-scheduling survey for Toronto, Canada, area: design and assessment. *Transp. Res. Rec.* 1894, 140–149. <https://doi.org/10.3141/1894-15>
- Donges, J.F., Schultz, H.C.H., Marwan, N., Zou, Y., Kurths, J., 2011. Investigating the topology of interacting networks. *Eur. Phys. J. B* 84, 635–651. <https://doi.org/10.1140/epjb/e2011-10795-8>
- Dunbar, R.I., 2016. Do online social media cut through the constraints that limit the size of offline social networks? *R. Soc. Open Sci.* 3, 150292. <https://doi.org/10.1098/rsos.150292>
- Dunbar, R.I., Arnaboldi, V., Conti, M., Passarella, A., 2015. The structure of online social networks mirrors those in the offline world. *Soc. Netw.* 43, 39–47. <https://doi.org/10.1016/j.socnet.2015.04.005>
- Ernst, O., Doucet, B., 2014. A window on the (changing) neighbourhood: The role of pubs in the contested spaces of gentrification. *Tijdschr. Voor Econ. En Soc. Geogr., Contemporary gentrification* 105, 189–205. <https://doi.org/10.1111/tesg.12071>

- Farber, S., Neutens, T., Carrasco, J.-A., Rojas, C., 2014. Social interaction potential and the spatial distribution of face-to-face social interactions. *Environ. Plan. B Plan. Des.* 41, 960–976. <https://doi.org/10.1068/b120034p>
- Freeman, L.C., 2004. *The Development of Social Network Analysis: A Study in the Sociology of Science*. Empirical Press, Vancouver.
- Fu, Y., 2005. Measuring personal networks with daily contacts: a single-item survey question and the contact diary. *Soc. Netw.* 27, 169–186. <https://doi.org/10.1016/j.socnet.2005.01.008>
- Gehl, J., 2011. *Life between buildings: using public space*. Island Press.
- Golledge, R.G., Stimson, R.J., 1996. *Spatial Behavior: A Geographic Perspective*. The Guilford Press.
- Guimera, R., Amaral, L.A.N., 2005. Cartography of complex networks: modules and universal roles. *J. Stat. Mech. Theory Exp.* 2005, P02001. <https://doi.org/10.1088/1742-5468/2005/02/p02001>
- Guimerà, R., Amaral, L.A.N., 2005. Functional cartography of complex metabolic networks. *Nature* 433, 895. <https://doi.org/10.1038/nature03288>
- Habib, K.M.N., Carrasco, J.-A., 2011. Investigating the role of social networks in start time and duration of activities: Trivariate simultaneous econometric model. *Transp. Res. Rec.* 2230, 1–8. <https://doi.org/10.3141/2230-01>
- Hägerstrand, T., 1970. What about people in regional science?, in: *Papers in Regional Science*. pp. 7–24. <https://doi.org/10.1111/j.1435-5597.1970.tb01464.x>
- Hampton, K.N., Sessions, L.F., Her, E.J., Rainie, L., 2009. Social isolation and new technology. *Pew Internet Am. Life Proj.* 4.
- Hickman, P., 2013. “Third places” and social interaction in deprived neighbourhoods in Great Britain. *J. Hous. Built Environ.* 28, 221–236. <https://doi.org/10.1007/s10901-012-9306-5>
- Hinckson, E.A., Duncan, S., Oliver, M., Mavoa, S., Cerin, E., Badland, H., Stewart, T., Ivory, V., McPhee, J., Schofield, G., 2014. Built environment and physical activity in New Zealand adolescents: a protocol for a cross-sectional study. *BMJ Open* 4, e004475. <http://dx.doi.org/10.1136/bmjopen-2013-004475>
- Holt-Lunstad, J., Smith, T.B., Baker, M., Harris, T., Stephenson, D., 2015. Loneliness and Social Isolation as Risk Factors for Mortality: A Meta-Analytic Review. *Perspect. Psychol. Sci.* 10, 227–237. <https://doi.org/10.1177/1745691614568352>
- Holt-Lunstad, J., Smith, T.B., Layton, J.B., 2010. Social Relationships and Mortality Risk: A Meta-analytic Review. *PLOS Med* 7, e1000316. <https://doi.org/10.1371/journal.pmed.1000316>
- Hristova, D., Williams, M.J., Musolesi, M., Panzarasa, P., Mascolo, C., 2016. Measuring urban social diversity using interconnected geo-social networks, in: *Proceedings of the 25th International Conference on World Wide Web*. pp. 21–30.
- Jia, P., Xue, H., Yin, L., Stein, A., Wang, M., Wang, Y., 2019. Spatial technologies in obesity research: current applications and future promise. *Trends Endocrinol. Metab.* 30, 211–223. <https://doi.org/10.1016/j.tem.2018.12.003>

- Kestens, Y., Chaix, B., Gerber, P., Desprès, M., Gauvin, L., Klein, O., Klein, S., Köppen, B., Lord, S., Naud, A., Payette, H., Richard, L., Rondier, P., Shareck, M., Sueur, C., Thierry, B., Vallée, J., Wasfi, R., 2016. Understanding the role of contrasting urban contexts in healthy aging: an international cohort study using wearable sensor devices (the CURHA study protocol). *BMC Geriatr.* 16, 96–108. <https://doi.org/10.1186/s12877-016-0273-7>
- Kestens, Y., Thierry, B., Shareck, M., Steinmetz-Wood, M., Chaix, B., 2018. Integrating activity spaces in health research: Comparing the VERITAS activity space questionnaire with 7-day GPS tracking and prompted recall. *Spat. Spatio-Temporal Epidemiol.* 25, 1–9. <https://doi.org/10.1016/j.sste.2017.12.003>
- Kestens, Y., Wasfi, R., Naud, A., Chaix, B., 2017. “Contextualizing Context”: Reconciling Environmental Exposures, Social Networks, and Location Preferences in Health Research. *Curr. Environ. Health Rep.* 4, 51–60. <https://doi.org/10.1007/s40572-017-0121-8>
- Kim, J., Rasouli, S., Timmermans, H.J., 2018. Social networks, social influence and activity-travel behaviour: a review of models and empirical evidence. *Transp. Rev.* 38, 499–523. <https://doi.org/10.1080/01441647.2017.1351500>
- Kivelä, M., Arenas, A., Barthelemy, M., Gleeson, J.P., Moreno, Y., Porter, M.A., 2014. Multilayer networks. *J. Complex Netw.* 2, 203–271. <https://doi.org/10.1093/comnet/cnu016>
- Krempel, L., Scott, J., Carrington, P.J., 2011. Network Visualization, in: *The SAGE Handbook of Social Network Analysis*. SAGE publications, pp. 558–577.
- Kwan, M.-P., 2009. From place-based to people-based exposure measures. *Soc. Sci. Med.* 69, 1311–1313. <https://doi.org/10.1016/j.socscimed.2009.07.013>
- Kweon, B.-S., Sullivan, W.C., Wiley, A.R., 1998. Green common spaces and the social integration of inner-city older adults. *Environ. Behav.* 30, 832–858. <https://doi.org/10.1177/001391659803000605>
- Latapy, M., Magnien, C., Vecchio, N.D., 2008. Basic notions for the analysis of large two-mode networks. *Soc. Netw.* 30, 31–48. <https://doi.org/10.1016/j.socnet.2007.04.006>
- Lee, J.Y., Kwan, M.-P., 2011. Visualisation of socio-spatial isolation based on human activity patterns and social networks in space-time. *Tijdschr. Voor Econ. En Soc. Geogr.* 102, 468–485. <https://doi.org/10.1111/j.1467-9663.2010.00649.x>
- Leyden, K.M., 2003. Social Capital and the Built Environment: The Importance of Walkable Neighborhoods. *Am. J. Public Health* 93, 1546–1551. <https://doi.org/10.2105/AJPH.93.9.1546>
- Liu, D., Ainsworth, S.E., Baumeister, R.F., 2016. A meta-analysis of social networking online and social capital. *Rev. Gen. Psychol.* 20, 369–391. <https://doi.org/10.1037/gpr0000091>
- Liu, X., Murata, T., 2009. Community Detection in Large-Scale Bipartite Networks, in: *Proceedings of the 2009 IEEE/WIC/ACM International Joint Conference on Web Intelligence and Intelligent Agent Technology - Volume 01, WI-IAT '09*. IEEE Computer Society, Washington, DC, USA, pp. 50–57. <https://doi.org/10.1109/WI-IAT.2009.15>

- Marin, A., Wellman, B., 2011. Social Network Analysis: An Introduction, in: Scott, J., Carrington, P.J. (Eds.), *The SAGE Handbook of Social Network Analysis*. SAGE publications, pp. 11–25.
- Marsden, P.V., 2005. Recent Developments in Network Measure, in: Carrington, P.J., Scott, J., Wasserman, S. (Eds.), *Models and Method in Social Network Analysis*. Cambridge University Press, pp. 8–30.
- Marsden, P.V., 1990. Network Data and Measurement. *Annu. Rev. Sociol.* 16, 435–463.
<https://doi.org/10.1146/annurev.so.16.080190.002251>
- Mason, M.J., Valente, T., Coatsworth, J.D., Mennis, J., Lawrence, F., Zelenak, P., 2010. Place-Based Social Network Quality and Correlates of Substance Use Among Urban Adolescents. *J. Adolesc.* 33, 419–427.
<https://doi.org/10.1016/j.adolescence.2009.07.006>
- Mastrandrea, R., Fournet, J., Barrat, A., 2015. Contact Patterns in a High School: A Comparison between Data Collected Using Wearable Sensors, Contact Diaries and Friendship Surveys. *PLoS One* 10, e0136497.
<https://doi.org/10.1371/journal.pone.0136497>
- Milardo, R.M., 1992. Comparative Methods for Delineating Social Networks. *J. Soc. Pers. Relatsh.* 9, 447–461.
<https://doi.org/10.1177/0265407592093007>
- Newman, M., 2018. *Networks*. Oxford university press.
- Oldenburg, R., 1999. *The great good place: Cafes, coffee shops, bookstores, bars, hair salons, and other hangouts at the heart of a community*. Da Capo Press.
- OpenStreetMap Contributors, 2012. OpenStreetMap.
- Palmer, C., Ziersch, A., Arthurson, K., Baum, F., 2005. “Danger lurks around every corner”: fear of crime and its impact on opportunities for social interaction in stigmatised Australian suburbs. *Urban Policy Res.* 23, 393–411.
<https://doi.org/10.1080/08111470500354216>
- Pelechrinis, K., Krishnamurthy, P., 2016. Socio-spatial affiliation networks. *Comput. Commun.* 73, 251–262.
<https://doi.org/10.1016/j.comcom.2015.06.002>
- Perchoux, C., Chaix, B., Kestens, Y., 2019. Activity spaces in place and health research: Novel exposure measures, data collection tools, and designs. *Health Place* 58, 102130. <https://doi.org/10.1016/j.healthplace.2019.05.008>
- Perchoux, C., Kestens, Y., Brondeel, R., Chaix, B., 2015. Accounting for the daily locations visited in the study of the built environment correlates of recreational walking (the RECORD Cohort Study). *Prev. Med.* 81, 142–149.
<https://doi.org/10.1016/j.yjmed.2015.08.010>
- Phithakkitnukoon, S., Smoreda, Z., Olivier, P., 2012. Socio-geography of human mobility: A study using longitudinal mobile phone data. *PloS One* 7, e39253. <https://doi.org/10.1371/journal.pone.0039253>

- Picornell, M., Ruiz, T., Lenormand, M., Ramasco, J.J., Dubernet, T., Frías-Martínez, E., 2015. Exploring the potential of phone call data to characterize the relationship between social network and travel behavior. *Transportation* 42, 647–668. <https://doi.org/10.1007/s11116-015-9594-1>
- R Core Team, 2013. *R: A language and environment for statistical computing*.
- Rainie, H., Wellman, B., 2012. *Networked: The new social operating system*. Mit Press Cambridge, MA.
- Requena, F., Ayuso, L., 2019. Individualism or complementarity? The effect of digital personal networks on face-to-face personal networks. *Inf. Commun. Soc.* 22, 2097–2111. <https://doi.org/10.1080/1369118X.2018.1477968>
- Roberts, S.B., Dunbar, R.I., 2015. Managing relationship decay. *Hum. Nat.* 26, 426–450. <https://doi.org/10.1007/s12110-015-9242-7>
- Rosenbaum, M.S., 2006. Exploring the social supportive role of third places in consumers' lives. *J. Serv. Res.* 9, 59–72. <https://doi.org/10.1177/1094670506289530>
- Schmidt, T., Kerr, J., Kestens, Y., Schipperijn, J., 2018. Challenges in using wearable GPS devices in low-income older adults: Can map-based interviews help with assessments of mobility? *Transl. Behav. Med.* 9, 99–109. <https://doi.org/10.1093/tbm/iby009>
- Scott, J., Carrington, P.J. (Eds.), 2011. *The SAGE handbook of social network analysis*. SAGE publications.
- Shakya, H.B., Christakis, N.A., Fowler, J.H., 2017. An exploratory comparison of name generator content: Data from rural India. *Soc. Netw.* 48, 157–168. <https://doi.org/10.1016/j.socnet.2016.08.008>
- Smieszek, T., Barclay, V.C., Seeni, I., Rainey, J.J., Gao, H., Uzicanin, A., Salathé, M., 2014. How should social mixing be measured: comparing web-based survey and sensor-based methods. *BMC Infect. Dis.* 14, 136. <https://doi.org/10.1186/1471-2334-14-136>
- Smith, L., Foley, L., Panter, J., 2019. Activity spaces in studies of the environment and physical activity: A review and synthesis of implications for causality. *Health Place* 102113. <https://doi.org/10.1016/j.healthplace.2019.04.003>
- Srinivasan, S., Bhat, C.R., 2008. An exploratory analysis of joint-activity participation characteristics using the American time use survey. *Transportation* 35, 301–327. <https://doi.org/10.1007/s11116-007-9155-3>
- Stewart, T., Duncan, S., Chaix, B., Kestens, Y., Schipperijn, J., Schofield, G., 2015. A novel assessment of adolescent mobility: a pilot study. *Int. J. Behav. Nutr. Phys. Act.* 12, 18. <https://doi.org/10.1186/s12966-015-0176-6>
- Stopher, P.R., 1992. Use of an activity-based diary to collect household travel data. *Transportation* 19, 159–176. <https://doi.org/10.1007/BF02132836>
- Toole, J.L., Herrera-Yaqué, C., Schneider, C.M., González, M.C., 2015. Coupling human mobility and social ties. *J. R. Soc. Interface* 12, 20141128. <https://doi.org/10.1098/rsif.2014.1128>

Umberson, D., Karas Montez, J., 2010. Social relationships and health: A flashpoint for health policy. *J. Health Soc. Behav.* 51, S54–S66. <https://doi.org/10.1177/0022146510383501>

van den Berg, P., Arentze, T., Timmermans, H., 2010. Location-type choice for face-to-face social activities and its effect on travel behavior. *Environ. Plan. B Plan. Des.* 37, 1057–1075. <https://doi.org/10.1068/b36019>

Vasylyeva, T.I., Friedman, S.R., Paraskevis, D., Magiorkinis, G., 2016. Integrating molecular epidemiology and social network analysis to study infectious diseases: towards a socio-molecular era for public health. *Infect. Genet. Evol.* 46, 248–255. <https://doi.org/10.1016/j.meegid.2016.05.042>

Wang, D., Pedreschi, D., Song, C., Giannotti, F., Barabasi, A.-L., 2011. Human Mobility, Social Ties, and Link Prediction, in: *Proceedings of the 17th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, KDD '11*. ACM, New York, NY, USA, pp. 1100–1108. <https://doi.org/10.1145/2020408.2020581>