The Complexity of Social Networks in Healthy Aging: Novel Metrics and Their Associations with Psychological Well-Being

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Abstract:

Social networks play a crucial role in promoting healthy aging, yet the intricate mechanisms connecting social capital to health present a complex challenge. Additionally, the majority of social network analysis studies focusing on older adults typically concentrate on the participants' individual relationships, often overlooking the interconnections between these relationships. In this study, we went further than current ego-centered network studies by determining global social network metrics and the structure of relationships among older adult participants of the RECORD Cohort using the Veritas-Social questionnaire. The aim of this study is to identify key dimensions of social networks of older adults, and to evaluate how these dimensions relate to depressive symptoms, life satisfaction, and well-being. Using Principal

Component Analyses (PCA), we identified four social network dimensions with psychological meanings. Dimension 1 (homophily) was positively linked with perceived accessibility to services in one's residential neighborhood but this same dimension was negatively linked with the level of study (i.e., Bachelor, Master, PhD, etc.). Dimension 2 (social integration) a~~s~~nd Dimension 3 (social support) were~~as~~ only linked to the number of people living (being in the same residence) with ego (i.e. the interviewed participant). Dimension 4 was linked with perceived accessibility to local services. Finally, and rather surprisingly, we found that none of the four network dimensions, even the degree, were~~as~~ linked to the three health status metrics.

Keywords: elderly, social support, social relationships, mental health, physical health

Introduction

Influence of social relationships on human health has been widely studied for decades. Since the seminal work on social integration and all-cause mortality (House et al., 1988), a large body of research has shown that a lack of positive social relationships is a risk factor for all-cause mortality (Holt-Lunstad et al., 2010) with effect sizes comparable to or greater (although perhaps less consistent, meaning with more individual variations) than those~~at~~ of smoking and obesity (Carter et al., 2015; Flegal et al., 2013). There is also strong and ~~repeated~~ multiple evidence linking social relationships to various disease-related outcomes; however, the mechanisms that explain these associations remain largely unknown and likely involve a series of complex and intertwined behavioral, psychological, and biological pathways (Berkman et al., 2014; Sueur et al., 2021~~a~~).

These complex relationships between social networks and health persist in later life (Rook, 2015), suggesting that positive social relationships may be an important factor in promoting healthy aging. Nevertheless, a difficulty in gerontological research is that individuals—even those from the same population—exhibit great variability in their rate of aging. ‘Aging differently’ means that at the same chronological age (e.g. 81 years), we may not have the same health status and/or mortality risk (i.e., biological aging). This variability is multifactorial, with a range of causes, including the physical design and structure of cities and buildings (the built environment)~~the built environment~~, sociodemographic factors, mobility, and social networks. What is more, successful aging also means ‘aging in place’, that is, having the resources and ability to live in one’s own home and community. Aging in place is generally what older adults want—it sustains the sense of belonging to a community and favors the maintenance of social ties (Gardner, 2011; Rook, 2015), two dimensions associated with positive outcomes, including better physical and mental health, lower stress, physical activity, and survival. Social isolation and perceived loneliness can be particularly ~~deleterious~~ detrimental in old age. Both dimensions increase the risk of depression and contribute to cognitive decline, diminished immune function, and all-cause mortality (Barnes et al., 2004; Cacioppo et al., 2006; Giles et al., 2005; Uchino, 2006).

The mechanisms linking social network dimensions to healthy aging are complex. Social networks, participation, integration, and support are distinct concepts that interact in a complex dynamic system. Social networks encompass the aggregation and portrayal of social relationships. Social support encompasses emotional, social, physical, and financial assistance, while social engagement involves participation in various activities. Social connectedness is characterized by the sense of being cared for and experiencing a sense of belonging. Finally, social integration was considered to be related to the sense of belonging to a social network. Some social network characteristics have been linked to positive social integration and participation (Berkman et al., 2014); social network size increases the likelihood of engagement and social participation and promotes the development of a sense of community belonging (Bell, 1998; Wilkinson, 1991), which, in turn, increases the perception of social integration.

Differently, social participation opens up opportunities to create new relationships and expand one's social network (Stern et al., 2011). However, network size does only seem to be positively linked to social support to a certain extent (Seeman & Berkman, 1988; Wellman, 1992). Based on a Dutch sample, Aartsen et al. (2004) found that as adults age, their networks increasingly consist of family members, and network size influences or is influenced by personal cognitive and physical decline. Recent research has emphasized the type and structure of social networks in which older adults are embedded and their implications for health. Litwin and Shiovitz-Ezra (2006), for instance, found that the association between network type and mortality was important primarily for persons aged 70 years and older; those in diverse, friend-focused, and, to a lesser extent, community-clan networks experienced a lower risk of all-cause mortality. Similarly, Cornwell (2009) examined the patterns of network bridging among older adults, hypothesizing that individuals who occupy bridge positions within their networks benefit from improved access to diverse resources and better control over the exchange of information and resources among network members. Cornwell (2009) found that older adults are more likely to serve as bridges, as measured through the betweenness coefficient if they exhibit good cognitive and functional health. While we analyzed correlations between network indices and well-being of people in France (Fancello et al., 2023; Fernandes et al., 2021) or in Canada (Kestens et al., 2016; Naud et al., 2020), we need more formal social network analyses (more quantitative and less subjective) to establish the links between participant characteristics, their relationships, and their health and well-being.

This paper addresses two important methodological issues, one about the statistical interdependence of network measures, one about the dependence of these measures with healthy aging. Usually correlations are made between different network metrics and measures of wellbeing but many social network indices are dependent and this may lead to false positive results and ~~wrong~~ incorrect conclusions (Sosa et al., 2020, 2021). In this paper, we adopted a new way to test data in order to avoid this data interdependence and potentially false positives and false negatives. Some studies already address this dependence of network measures. Vacca (2020) introduced an innovative method for identifying structural typologies in personal networks, highlighting the considerable impact of personal network structure — the interconnections among an individual's contacts — on social outcomes. This method was contrasted with another recent approach, revealing that while both effectively capture variations in network structures, they also show significant discrepancies and cross-classification. These findings hold promise for future research in areas such as personal communities, social support, and social capital. ~~introduced a new method for identifying structural typologies in personal networks, emphasizing that personal network structure, or how individuals' contacts are connected to each other, has a significant impact on social outcomes, and the new method is compared to another recently introduced approach, finding that both methods effectively capture variation in network structures but also exhibit substantial disagreement and cross-classification, with potential applications in researching personal communities, social support, and social capital.~~ Bidart et al. (2018) introduced a typology of personal networks, constructed from detailed data on young French individuals in a longitudinal study, which relies on a limited set of indicators related to the structure of relationships between individuals, with the goal of creating a generalizable approach applicable to different surveys. Finally, Charbey & Prieur, (2019) applied a network science approach, drawing from methods in various disciplines, to analyze around 10,000 non-overlapping Facebook ego networks collected through a survey application, utilizing a concept called 'graphlet representativity' to classify these networks more effectively, resulting in two clusterings: one of graphlets or network motifs (paths, star-like, holes, light triangles, and dense) and one of the networks, revealing distinct structural characteristics of the Facebook ego networks, and discussing differences between results obtained using 4-node and 5-node graphlets or network motifs, with potential follow-up directions in sociology and network science. Daatland & Lowenstein (2005), based on a sample of 6,106 urban individuals aged ~~25+~~25 and above in five countries, explored intergenerational family solidarity across different family cultures and welfare state regimes, finding that the welfare state has not diminished family involvement in elder care, but has encouraged more independent relationships between generations. Wyngaerden et al.(2019) investigated the relationship between network cohesion and continuity of care for 380 severely mentally ill ~~users~~ participants in Belgium, finding that cohesion indicators, such as density and egobetweenness, are relevant only for those with high-severity issues, irrespective of their living arrangements, and that optimal continuity of care is associated with fewer professionals or services in the user's network and a dense network for users with the most severe problems, suggesting the need for adaptable interventions as severity changes.

Most of social network analyses (SNA) ~~studies~~ considered only participants' relationships and not how these relationships are themselves connected independent of ego but not the connections between participants' relationships. Indeed, social integration is dependent on how participants and their relationships are connected (Brissette et al., 2000). Sense of belonging or belongingness, which can be measured through the density or transitivity (i.e. triangle of connections between three persons) of networks of relationships, has been negatively associated with depression (Hagerty & Williams, 1999). Therefore, from a public health standpoint, it is essential to identify how social network metrics are linked to each other (e.g. how transitivity influences degree) and how this interplay is correlated with social capital among older adults. This requires measuring complex and indirect relationships or what is commonly referred to as 'a friend of a friend'. In social network analysis, metrics based only on a participant's relationships are called first-order metrics, whereas those that depend on the relationships of relationships are called second-order metrics (Sosa et al., 2021). The protocol to measure first- and second-order metrics was first developed through the CURHA (Contrasted Urban settings for Healthy Aging) study using the VERITAS-Social questionnaire (Kestens et al., 2016; Naud et al., 2020). The questionnaire presents questions about ~~‘where’~~in which places in the city a number of activities are conducted, to which a social network module was added. When respondents document a given destination, they are also asked to provide information on contacts from their network with whom they usually visit that destination. At the end of the questionnaire, participants are presented with all network members identified throughout the spatial questionnaire and asked to identify with whom they discuss important matters and with whom they like to socialize, and they may further add new network members at that step. Finally, they were asked to document who in their network knows whom. These questions identify relationships between network members, going a step further than current ego-centered network classic studies, and allowing global social network metrics and the structure of relationships among participants’ first order contacts (Naud et al., 2020).

In this paper, we present various social network metrics that this SNA data enables, and how metrics are correlated together. In our study, we employed a range of network indices to investigate the complex dynamics of social networks among older adults, with each index serving a distinct purpose. Simmelian brokerage, as one of our chosen measures, provided unique insights into the role of participants (egos) as brokers in the network, shedding light on the potential fragmentation of network components when egos are removed (Krackhardt, 1999; Krackhardt & Kilduff, 2002). This index, while less commonly employed in sociology, was selected due to its ability to combine elements of both betweenness and the clustering coefficients, offering a more comprehensive view of network structure. Additionally, our study incorporated other well-established indices, such as degree centrality, which measured the number of connections participants had with other network members, and network density, assessing the overall interconnectedness of the network (Borgatti et al., 2009; Newman, 2010a; Scott, 2000; Sosa et al., 2021; Wasserman & Faust, 1994). The global clustering coefficient was used to gauge the extent to which cohesive structures formed within the network. Furthermore, the diversity index allowed us to examine the diversity of connections across different categories of people (Newman, 2006). Together, these indices provided a multifaceted approach to comprehensively explore the structure, diversity, and dynamics of social networks among older adults, offering a more nuanced understanding of the factors influencing their social interactions and potential impacts on well-being. Roucolle et al. (2020) stipulated that there are difficulties of capturing the network complexity in a simple manner. While Simmelian brokerage may not have enjoyed the same recognition as some traditional measures, our study aimed to broaden the scope of methodologies in the field, opening avenues for future research to delve deeper into these intricate network dynamics. Statistically speaking, it is not logical to separately test the effects of two independent variables on one different dependent variable in distinct tests, as we cannot determine whether these two dependent variables exhibit collinearity, which may result in false positives. Similarly, it is inadvisable to test the effects of two collinear independent variables on a dependent variable in a same model, as this could lead to false negatives by nullifying the genuine impact of one factor. This is why in this paper we initially examined variable correlations and employed a principal component analysis (PCA) to identify which dependent variables contribute to the dimensions revealed by PCA and to elucidate their implications. In addition, and more importantly, we ascertain how these different social network metrics can relate to measures of depression and general well-being. The aim of this study is to assess how social network metrics are intertwined thanks to Principal Component Analyses (PCA) (Roucolle et al., 2020), to identify key dimensions of social networks of older adults, and to evaluate how these dimensions relate to depressive symptoms, life satisfaction, and well-being but also how socio-demographic factors (participants socioeconomic profiles and characteristics of residential neighborhood) may influence the social network of participants.

1. Methods

a. Study population

We employed data from a survey conducted between September 2019 and March 2020 that was administered to 73 older adults (aged 60 and over) residing in the Paris region (Île-de-France). We initially had a larger sample size, but our study was impacted by the COVID-19 pandemic, so we chose to focus solely on a pre-COVID-19 period for this study. This event and this choice explain our low sample size. These participants were recruited from the RECORD Cohort (Chaix, Kestens, Bean, et al., 2012). Using the framework of the Healthy Aging and Networks in Cities (HANC) and Promoting Mental Well-Being and Healthy Aging in Cities (MINDMAP) projects, this survey provides information on participants' socioeconomic profiles, their residential neighborhoods, and their regular social visited locations (Fernandes et al., 2021; Kestens et al., 2016). VERITAS is an interactive map-based questionnaire that allows participants to draw the limits of their perceived neighborhood and locate their regular activities (Chaix, Kestens, Perchoux, et al., 2012). Moreover, a social network component allows participants to describe each member of their social network (sociodemographic profile and their residence place) and how they are connected. It further collects data about the level of inter-knowledge of social network members and asks to specify places visited together (see Kestens et al., 2016) for a detailed explanation of the questionnaire). Finally, data from the National Institute of Statistics Economic Studies and the National Institute of Geography were used to derive socioeconomic, demographic and built environment characteristics and perceived neighborhoods.

b. Measures

These data allowed us to analyze a set of indicators regarding social network structural characteristics, sociodemographic and residential factors, and health status.

- **Participants' socioeconomic profiles** were defined through the following variables: age, gender, household income per capita (seven categories: <500, 500–1,000, 1,000–1,500, 1,000–2,000, 2,000–3,000, 3,000–4,000, and >4000); educational attainment (four categories: no education, primary education, secondary education, higher education); marital status (single or a couple); household type (number of people living with the interviewed person); and employment status. A summary of the data is provided in Table 1.
- **Characteristics of residential neighborhoods** were defined from a combination of objective and subjective variables. Objective variables include location (Paris, close suburb, far suburb), neighborhood demographic and socioeconomic condition (average income, aging index, and population density), and urban walkability variables (density and diversity of services and street intersection density). Additionally, we investigated the following subjective variables obtained from self-report: urban quality (see T~~t~~able 2), pedestrian accessibility, social support, and neighborhood safety. These indicators represent environmental opportunities (i.e. resources) in participants' neighborhoods and ~~to~~ unveil the motivations that lead people to select a specific environment (internal or external to their residential neighborhood) for social activities. A summary of the data is provided in T~~t~~able 2.

  We examined whether neighborhood measures showed high correlations, but this was not the case (Fig. S1). The highest correlation (R^2) was 0.63, while collinearity is typically considered to be present when correlations are approximately 0.9 or higher (Franke, 2010).
- **Structure of social networks.** We are working on networks composed of a focal node (the ego) and its connected social members (alters). Among the social network measures, we are interested in evaluating the characteristics that we postulate can be related to older adults' well-being:

a) the number of social network members (i.e. the network degree);

b) the strength of contact with social network members—1.) by face-to-face contact only or 2.) by all contacts (mail, phone call, face-to-face)—approximated through the number of contacts per week;

c) the level of connection between the social members (i.e. the network density): we calculated this density with and without the presence of ego in the network to avoid correlation with other network measures;

d) the centrality of the participant with respect to his/her social network (i.e. Simmelian brokerage);

e) the presence of closed cohesive structures among social network members (i.e. clustering coefficient);

f) the diversity of people in a social network (the Evenness Index and Assortativity Index for age, sex, occupation, and level of study).

We provide a summary of these data and definitions in T~~t~~able 3.

- **Health status.** Participants provided answers to the following tests (see T~~t~~able 4 for definitions): the CES-20 item test (Center for Epidemiological Studies Depression Scale (Radloff, 1977)), the CASP-12 scale test (Quality of life, Hyde et al., 2003), and the STAI Y-B test (Spielberger et al., 1983). We calculated the corresponding health status indices (see T~~t~~able 4).

c. Statistical analyses

We first performed a correlation analysis using the R package PerformanceAnalytics (Carl et al., 2010; Peterson et al., 2018) (to check whether some variables were highly correlated (variables with $r > 0.9$)) (first, socioeconomic ones and second network ones, in two different

PCA). Concerning network variables, because of the high correlations between network density and Simmelian brokerage and the clustering coefficient, we also decided to correct the Simmelian brokerage and the clustering coefficient by performing a linear regression with these two metrics as the response variable and network density as an explanatory factor. We took the residuals from this linear regression of the two metrics, which correspond~~s~~ to the variance of each point not explained by the network density, and created two new variables: res(simbrok) and res(clustcoeff). The correlations of these new variables with other network metrics are given in Fig. S2.

The next steps only concerned the network variables. We conducted a Principal Component Analysis (PCA) with Varimax rotation using the Psych R package (Revelle, 2011; Revelle & Revelle, 2015). PCA is a statistical technique employed to reduce the number of variables into more biologically, psychologically, or socially interpretable dimensions. Prior to analysis, the variables were automatically adjusted by centering them around their means for comparability in terms of mean and range. Four dimensions were retained based on eigenvalues exceeding the threshold of 1, a commonly accepted practice (Budaev, 2010; Holland, 2008; Smith, 2002). The application of Varimax rotation aimed to simplify the representation of a specific subspace using only a select set of key items. Essentially, Varimax rotation maximizes the explained variance by adjusting the variables' positions on the dimensions. We then assessed the loading of each variable on each dimension, which represented the coefficients of the linear combination from which the principal components were derived. These loadings were obtained by dividing the coordinates of the variables by the square root of the eigenvalue linked to the respective component. Variables with loadings below 0.6, indicating a limited contribution to each dimension and the overall explained variance, were subsequently eliminated. The resulting four new dimensions were employed as variables in our subsequent analyses.We used linear regression model selection and multi-model inference (Burnham &

Anderson, 2004) to test the links of sociodemographic variables with network metrics and we used Poisson models to test the effect of network metrics on health status. We used the four network dimension values to better understand the interplay between participants' social environments, their networks, and their well-being, and we used the Poisson distribution with health status scores as the outcomes. We used the Gaussian distribution with the four network dimensions as the outcomes as they were normalized and scaled owing to the PCA.

We checked statistically several model assumptions (normality and homogeneity of residuals, variance inflation factors) and no obvious violations or influential cases were detected. We ran multi-model inferences to compare and rank candidate models according to (i) their respective Akaike information criteria after correction for small sample sizes (AICc) and (ii) normalized Akaike weights (AICw) (Burnham & Anderson, 2004). ΔAICc is the difference in AICc between a given model and the model with the lowest AIC value. The AIC weight indicates the probability that a given model is the best among candidate models. Models with a ΔAICc<4 were considered equally possible candidates and their statistics were averaged. The null model was also included as a possible candidate but was never among the models with the lowest AICc. The averaged model coefficients were obtained for models with ΔAICc<4. Model inference and averaging were performed using the R package MuMIn (Barton~~ń~~, 2013; Barton & Barton, 2013). This method allows us to find the independent variables that affect the response variable, even if they are covariant.

All analyses were performed using RStudio 1.4.1103 (Allaire, 2012; Racine, 2012). The significance threshold was set at $\alpha = 0.05$. Supplemental material, dataset and scripts are available on Zenodo: https://doi.org/10.5281/zenodo.7763430.

2. Results

a. Analyses of network indices

The strength of face-to-face contact was 9.9±5.9 contacts per week, whereas the strength of all contacts was 14.7±9.5 contacts per week. The degree of participants was 5.7±3.3 (i.e. relationships). Only one participant had a network with a degree of one, and the maximum degree was 19. The network density with ego was 0.79±0.23 and remained high without ego (0.68±0.34). The clustering coefficient of participants was 0.78±0.27 and the Simmelian brokerage was 2.4±2.29. The Everness Index equalled 0.51±0.20, and the assortativity, whatever the sociodemographic factor considered, was approximately -0.21±0.20.

The correlation chart (Fig. 1) shows two correlations with r > (-)0.9: between network density with ego and network density without ego (r=0.90), between network density without ego and the clustering coefficient (r=-0.94). Network density with ego and Simmelian brokerage were also significantly correlated (r=-0.84). These high correlations were due to the high connectivity between alters. Among the 73 participants, 34 (45%) had a network density (without ego) of 1. For the remaining participants, the difference in network density with and without ego was 0.18±0.11. Naturally, this difference in density with and without the presence of ego is directly due to the degree of participants: the higher the degree, the lower the probability of seeing all alters connected, and the lower the density (R^2=0.36, p<0.001). Removing ego from the network also increased the correlation between the network density and the clustering coefficient (from 0.74 to 0.94) as the density of networks in which alters were only connected to ego fell to 0, as their clustering coefficient after the removal. This occurred for five participants (see details in Fig. S3a). Removing these five individuals significantly increased the correlation between the latter variables (see Fig. S3b), indicating dependencies between these network metrics. Next, analyses were performed by removing the density without ego and by analyzing the residuals of the clustering coefficient and the Simmelian brokerage according to the density to test the part of the variance that is independent of network density.

We performed a PCA on all the network metrics that provided four dimensions (eigenvalue > 1 which is commonly accepted as significantly explaining the variance (Budaev, 2010; Holland, 2008; Smith, 2002)). The total explained variance was 78.4%. Some variables did not have any loadings superior to 0.6 in any of the four dimensions, and we decided to remove these—not only because of their low contribution but also because they bring noise to explanations of dimensions. These variables were degree (loading between 0.44 and 0.49), Everness Index (loading between 0.28 and 0.52), and assortativity according to education (loading between 0.11 and 0.38). We repeated the PCA and obtained a better explained variance of 85.8% (dimension 1 = 26.2%, dimension 2= 24.4%, dimension 3 = 18.1%, dimension 4 = 17.1%). Each remaining variable had a loading higher for one dimension compared to the other, which allowed us to group variables in each of the four dimensions (see Table 5). Dimension 1 is mainly weighted by all the assortativities and residuals of the clustering coefficient. Dimension 2 includes the network density, clustering coefficient, and Simmelian brokerage and corresponds to ego centrality. Dimension 3 has the two variables of strength of contact. Finally, Dimension 4 includes only the residuals of Simmelian brokerage.

b. Relation between sociodemographic variables and network dimensions and metrics

Dimension 1 (assortativity) was positively linked to perceived accessibility to services ($z=2.96$, $p=0.0003$) but negatively linked with the level of study ($z=2.01$, $p=0.045$) (see Table s1). Dimensions 2 (ego centrality) and 3 (strengths of connections) were positively linked with the number of people living with ego ($z=3.04$, $p=0.002$; see Tables s2 and s3). Dimension 4 (residuals of Simmelian brokerage) was linked with the perceived accessibility to services ($z=2.06$, $p=0.04$; Table s4). Finally, the degree was positively linked with the age of the participants ($z=2.34$, $p=0.02$) and negatively linked with the level of education ($z=2.85$, p=0.004), population density (z=2.2, p=0.027), and gender (men compared to women, z=2.43, p=0.015) (see Table s5).

c. Links between network dimensions, metrics and well-being

No associations were found between the social network dimensions, even the degree (removed from the PCA analysis), and our health measures (see Table 6). Moreover, only the two variables of the strength of contact are linked with the Depression Scale (CES-20). The other metrics are not linked with any of the three health status metrics (see Table S6). The strength of all contacts (direct and indirect) is positively linked with the depression scale (Z=3.22, p=0.001), whereas the strength of direct contact (only face-to-face, z=2.45, p=0.014) is negatively linked with the depression scale. Other network metrics taken individually are not linked with the three health status metrics. We also conducted a qualitative assessment, indicating depressed participants with a 1 and non-depressed participants with a 0, to examine the effects of network dimensions and indices on the depression scale. However, we did not observe any significant effects ($|z| < 1.5$, $p > 0.129$).

Discussion

This study aimed to examine the structure of the social network, its drivers, and the consequences of this structure on health using new methodologies that can be summarized in three points:

1. Knowing how the participants (ego) and their alters are connected thanks to VeritasSocial (Kestens et al., 2016; Naud et al., 2020). This new questionnaire allows for the measurement of new network metrics. Indeed, social integration is dependent on not only how participants are connected but also how their relationships are connected with each

other independently of ego (Brissette et al., 2000), which is also negatively linked to depression (Hagerty & Williams, 1999).

2. The importance of some network metrics can be measured by removing the influence of others as network density using as in this study linear regression. This parameter is linked to most other metrics as adding one connection in a network increases density as it increases indirect metrics (i.e., metrics that measure for ego how an individual's alters are connected). In our study, these indirect metrics were the clustering coefficient and the Simmelian brokerage. We then decided to extract the effect of density using residuals of the linear regression with indirect measures as response variables and density as a factor. This process seems scientifically viable as these residuals were important variables in the subsequent analyses.
3. PCA was performed on all network dimensions to find dimensions with psychological or sociological meanings by gathering the different metrics measured. PCA is used to reduce the number of estimators in one or several dimensions while retaining as much of the information as possible; the new resultant variable(s) are constructed as a linear combination of the original variables and allow the synthesis of all metrics (Berni et al., 2011a; Zass & Shashua, 2006). PCA also allows us to understand the different dimensions of a system and participants' social network and extract psychological or sociological meaning from these dimensions. ~~At~~ To our knowledge, PCA associated to SNA in order to highlight such dimensions was never done in health or gerontology research. In our study, we identified four network dimensions, which we explain in detail below.

Dimension 1 includes all the assortativities and residuals of the clustering coefficient. This corresponds simply to assortativity, the preference that participants attach to similar characteristics in other people (here, individuals of the same age, sex, and occupation). Dimension 2 includes the network density, clustering coefficient, and Simmelian brokerage and corresponds to ego centrality. Here, centrality concerns not only the direct and indirect connections—how ego is strongly connected—but also how one’s alters are connected. Dimension 2 fits the concept of social integration and is linked to social participation. Indeed, network density increases social participation (Wang et al., 2002) and promotes the development of a sense of community belonging (reflected in the clustering coefficient (Bell, 1998; Wilkinson, 1991)) and opens up new opportunities to create new relationships and expand one’s social network (i.e., the Simmelian brokerage (Stern et al., 2011)). Therefore, given that they mutually influence each other, it is logical that these metrics are gathered into one dimension. Dimension 3 includes the two strength of contact variables, meaning the strengths concerning all contacts (face-to-face and indirect) and the one for face-to-face contact only. It is interesting to see that these metrics are well separated from the other metrics, which implies that they do not reflect the same concept. Indeed, the strength or frequency of contact, whether direct or indirect, is the basis of social support (House et al., 1988; Wellman, 1992). Finally, Dimension 4 includes only the residuals of the Simmelian brokerage. Assessing what remains after removing the effect of network density from the Simmelian brokerage is not intuitive. The Simmelian brokerage is based on a complex value measure of Simmelian tie strength. Notably, while the basic ties are known as strong or weak and focus on the strength of the analyzed relationship, Simmelian ties are concerned with more than just the strength of the relationship; they examine the number of strong ties within a group. For a Simmelian tie to exist, there must be three (or more) reciprocal strong ties in a group (Krackhardt, 1999; Krackhardt & Kilduff, 2002). To understand this dimension more deeply, it is~~’s~~ important to recognize that the Simmelian brokerage metric is a complex value measure that assesses the strength of Simmelian ties. These ties extend beyond the simple strength of a relationship, taking into account the number of strong reciprocal ties within a group. In other words, Simmelian ties signify that there must be at least three or more mutual strong ties within a specific network group for them to exist. When considering the residuals of the Simmelian brokerage, we are essentially examining what remains after removing the influence of network density. Since these residuals form a distinct dimension, separate from assortativity (D~~d~~imension 1) and ego centrality (D~~d~~imension 2), it implies that they capture a specific aspect of connectivity or relationship dynamics that is not fully explained by either network density, the clustering coefficient, or Simmelian brokerage. While the exact interpretation of D~~d~~imension 4 may require further investigation and analysis, it suggests that it represents a unique feature of participants' social networks, potentially related to their social integration or network structure. Further research could help uncover the specific nature of this dimension and its implications for participants' well-being and social interactions.

PCA leads to the opportunity to have dimensions that give quantitative and objective measures to aspects as social support or social integration. On the basis of our better understanding of participants’ social network structure, we may now understand the drivers and consequences of these social networks. These analyses were conducted with results confirmed by the existing literature, which also yielded some contradictory results as we did not find some correlations between our dimensions and usual sociodemographic variables. First, Dimension 1 (assortativity or homophily) was positively linked with perceived accessibility to services in one’s residential neighborhood but negatively linked with the level of study. The higher the number of activities people who can perform near their residence, the more relationships they share with people who are similar to them in terms of age, education, or occupation. Because they can easily walk and join different services, they can meet their local counterparts who are more likely to be similar to them. However, the higher the level of education, the lower the homophily. This means that educated people show a greater diversity of relationships with people of different ages, education levels, or occupations. Dimension 2 (ego centrality or social integration) aand~~s~~ Dimension 3 (strengths of contacts or social support) were~~was~~ only linked to the number of people living with ego. This last result is logical and has been found in many studies (Hsieh & Zhang, 2021; Katayama et al., 2021; Lowndes et al., 2021; Seeman & Berkman, 1988; Zainuddin et al., 2020), but we expected to observe other influences, such as those from income, population density, urban quality, and accessibility (Kim et al., 2018; Sharmeen et al., 2014). Wood et al. (2010) for example, studied the association between sense of community, walking, and neighborhood design characteristics and found that the sense of community was enhanced by living in areas that encourage leisurely walking. However, a limited number of living areas are walkable, densely populated, and have a multiple choice of service contexts.[48] Carrasco et al. (2008) analyzed the spatial distribution of home locations of socialized social network members and found that a wider social network, frequent interactions, and greater distances are associated with people with high income. However, what we found by analyzing the degree of participants, was that older people, people with lower education, those living in lower population density areas, and females had higher degree networks. With age, while older adults show social selectivity (Sueur et al., 2021~~a~~), they are less dependent on time constraints and may see their families or other people at home more often (~~Agnete Aslaug~~ Kjær & Siren, 2020; Dupraz et al., 2020; Galof & Balantič, 2021). Dimension 4, which is linked to participants' social integration, was only linked with perceived accessibility to local services. The same explanations than for Dimension 1 apply. The higher the perceived pedestrian accessibility, the higher the number of participants who may go outside, may engage in different activities, and may be connected with different people. Similar results were reported by Buffel et al. (2014), who examined the relationship between subjective neighborhood perceptions and social participation among older adults living in medium-sized cities in Flanders, Belgium. They found that older adults reporting greater access to a larger number of services and amenities also reported higher levels of social participation.

Finally, and rather surprisingly, we found that none of the four aggregated network dimensions, even the degree, were~~as~~ linked to the three health status metrics. Only the strength of all contacts (direct and indirect) and the strength of direct contact were associated with the Depression Scale. However, the relationship was positive for all contacts and negative for face-to-face contact. This does not mean that direct contact leads to depression, but rather that it is likely that depressed participants often asked for face-to-face contacts with their family or friends to talk about their problems. However, indirect contact using social media or social technologies is increasingly important for older adults and is negatively linked with a sense of loneliness (Bonsaksen et al., 2021; Casanova et al., 2021; Schlomann et al., 2020; Silva et al., 2020). We found a link between health status and the strengths of contacts but not with degree or other network metrics. This is astonishing as several studies have shown a link between social capital (social network, social support, etc.) and different measures of physical and mental health. Our results may be due to our PCA to decrease the variance of explanatory variables and mask potentially existing associations. However, we also did not find relationships when network metrics were analyzed separately. Our sample size of 73 might also have been a limiting factor. This sample set is somewhat biased due to the setting of Paris, where the cost of living is quite high, which could decrease the variance of variables and, in turn, the possible effects of explanatory variables. Paris presents a unique setting for epidemiological research due to its densely populated urban environment, socioeconomic and cultural diversity, and access to healthcare services. The city's multicultural population and varying socioeconomic statuses introduce complexities in studying social networks and their associations with health. Factors like lifestyle, access to resources, and the cost of living in Paris can impact social network dynamics and health outcomes. Additionally, the city's public health initiatives and environmental factors, such as air quality and traffic congestion, play a role in the health of its residents. Researchers must consider these specific characteristics of Paris when conducting epidemiological studies to provide meaningful insights into the relationships between social networks and health.

We acknowledge the limitation of a small sample size, which can impact the generalizability and statistical power of the findings. A small sample size can lead to limited representativeness of the broader population, making it challenging to draw definitive conclusions that apply to a larger group of people. It can also affect the ability to detect statistically significant relationships or associations between variables. One other possible criticism is that the relationship between mental health and network features may not follow a linear pattern. Threshold effects could be at play, where certain network characteristics have a significant impact only once they cross a specific threshold. For example, complete social isolation may indeed have a detrimental effect on mental health, but having at least one friend could provide a protective effect against loneliness. The study's small sample size might not have been sufficient to detect such threshold effects. We checked however for sigmoid functions indicating a threshold effect and did not find such nonlinear data.. Further investigation into extreme cases or subgroup analysis could shed light on these nuances. By doing so, researchers could examine whether specific network characteristics have a more pronounced impact on those who are already experiencing higher levels of depression, potentially identifying critical thresholds or nonlinear relationships that might not be evident in the overall analysis. This approach could provide a deeper understanding of how social networks influence mental health and may help uncover patterns that were not apparent in the primary analysis due to the limitations of the small sample size. In this context, we recognize that the findings may not fully capture the complexity and nuances of social network dynamics and their impact on health, and that the results should be interpreted with caution. We emphasize the need for further research with larger and more diverse datasets to validate and extend their methodology, allowing for a more comprehensive understanding of social network structures, their determinants, and their consequences for various population groups. However we need to be careful about comparisons between studies. The purpose and methodologies of our study differ significantly from studies like Charbey & Prieur (2019) Vacca (2020), primarily because these studies also incorporate online and social media friends. This discrepancy is particularly relevant to the issue of defining social support, a concept we highlighted. In our research, we concentrated on tangible, physical, and psychological support, which naturally leads to a smaller number of network connections, or 'alters'. While studies with larger network sizes often offer greater applicability and generalizability, it is~~'s~~ important to recognize that smaller networks can still yield valuable insights into specific social dynamics and phenomena. Researchers should be diligent in designing their studies and carefully consider the network size that best aligns with their research objectives and constraints.

While our findings are limited, our study illustrates a new method to analyze social network metrics and better identify the different concepts of social capital (e.g. social support, social integration, Sueur et al., 2021a). Our methodology should be extended to other datasets to better understand the structure, drivers, and consequences of social networks of older adults and of people in general.

Conflicts of Interest

YK holds shares in Polygon Research Inc., the company that markets the VERITAS application. All other authors declare that they have no competing interests.

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Figure Captions

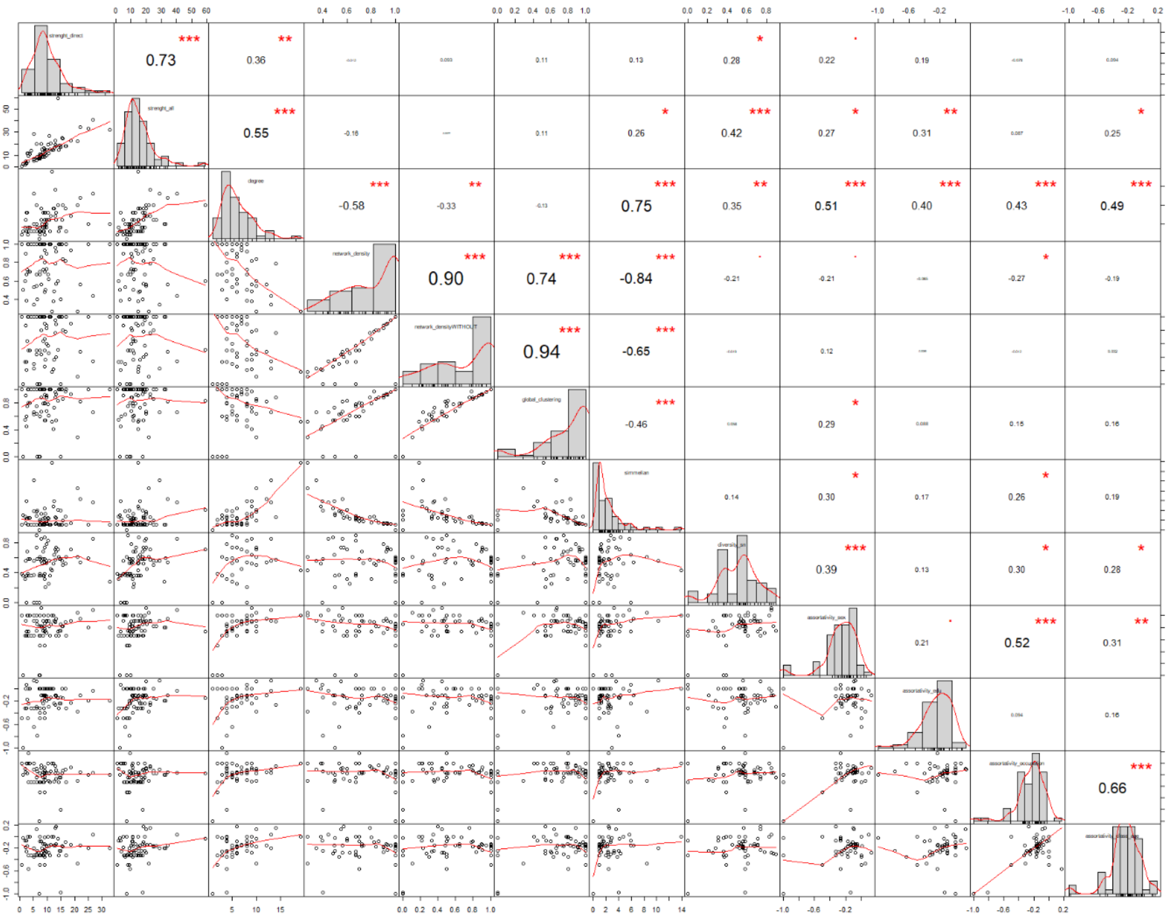

Figure 1: Correlation chart for the network metrics

Table Captions

Table 1: Socioeconomic and demographic variables.

Table 2: Residential neighborhood indicators

Table 3: Social network indicators

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Table 5: Loadings for each variable in each dimension of the PCA.

Table 6: Averaged statistical values following the model~~s~~ selection for the three health status as response variables and the four dimensions, plus the degree as independent variables

Tables

	Women %	***Men %***	***Sum %***
Sex	*36%*	*64%*	
Age			
>60 years	*13.3 %*	*24 %*	*37.3 %*
>70 years	*21.3 %*	*32 %*	*53.3 %*
>80 years	*1.3 %*	*8 %*	*9.3 %*
Income per capita (in €)			
500	*0 %*	*1.4 %*	***1.4*** *%*
500–1,000	*0 %*	*2.7 %*	***2.7*** *%*
1,000–1,500	*6.8 %*	*6.8 %*	***13.6*** *%*
1,500–2,000	*5.4 %*	*10.8 %*	***16.2*** *%*
2,000–3,000	*16.2 %*	*24.3 %*	***40.5*** *%*

3,000–4,000	*4.1 %*	*14.9 %*	***19** %*
>4,000	*4.1 %*	*2.8 %*	***6.9** %*
Employment status			
Stage	*0 %*	*0 %*	***0 %***
Worker	*0 %*	*9.3 %*	***9.3 %***
Unemployed	*0 %*	*0 %*	***0 %***
Retired	*34.7 %*	*53.3%*	***88 %***
Home Caretaker	*0 %*	*0 %*	***0 %***
Other	*1.3 %*	*1.3 %*	***2.6 %***
Level of education			
No education	*1.3%*	*2.7%*	***4%***
Primary education	*4%*	*1.3%*	***5.3%***
Secondary education	*13.3%*	*10.7%*	***24%***
Higher education	*17.3%*	*49.3%*	***66.6%***
Household size (n. individuals living with)			
Single~~olo~~	*18.7%*	*16.0%*	***34.7%***
Couple	*16.0%*	*36.0%*	***52.0%***
Family	*1.3%*	*12.0%*	***13.3%***
Depression status - CES D20 Index			
Not depressed (0–15)	*28.0%*	*60%*	***88%***
Depressed (>16)	*8%*	*4%*	***12%***
Anxiety – Stai Y B Index			
Not anxious	*33.2%*	*49%*	***82.2%***
Anxious (men>39; women >47)	*2.8%*	*15%*	***17.8%***

Table 2: Socioeconomic and demographic variables

Residential Neighborhood Indicators (the neighborhood area defined by the interviewed) (* Descriptive Variables; **Analytical Variables)					
Name	Indicator	Meaning	Resources	Source data	Mean
1. Location of the residence**	Proportion of the residential neighborhood within a specific class of municipality (based on population size): Paris center, medium suburbs, small suburbs, and rural communities.	Geographical location of the residential neighborhood with reference to the class of the municipality.	(Vallée et al., 2015)	INSEE	Paris center 37.33% Medium suburbs 30.67% Small suburbs 32.00%
2. Income**	Resident population's income pro capita.	The wealth of the resident people living in the neighborhood.		INSEE	31,376 €
3. Aging index**	Number of resident older adults (>65 years old) per	Represents the proportion of elderly population in the in the		INSEE	77.71

		100 persons younger than 17 years old.	space chosen by individuals to meet their social members.			
4.	Population density*	Geographic Information System processing: the resident population density.	The urban quality and the walkability of social places visited: density and diversity of services, density of population and density of intersections are related to a conducive walking environment.	(Cervero & Kockelman, 1997; Yue et al., 2017; Zandieh et al., 2017)	INSEE	17,344 ppl/km^2
5.	Density of services*	Geographic Information System processing: the number of places/km^2.	The density of services represents one of the variables of the urban quality and walkability of social places visited.		INSEE/BPE	23.3 places/km^2
6.	Diversity of services*	Geographic Information System processing: the	The diversity index represents one of the variables of the urban		INSEE/BPE	0.41

		Shannon Index normalized (Evenness Index).	quality and walkability of social places visited. It provides information about the urban composition by accounting for both abundance and evenness of the services present in space.	
7.	Street intersection density*	Geographic Information System processing: the ratio of intersections that are three or more ways per kilometer.	It is one of the most used walkability variables in the literature representing the street design and connectivity, block size, and the vitality of a place. Ewing and Cervero (2010) find that a 10% increase in intersections is linked to a 3.9% increase in walking.	196.89 km^2

8.	Urban quality **	Subjective urban quality: a total of 18 questions on a 4-point Likert scale. The higher the points, the greater the problems: the range is from 0 to 1.	The perceived urban quality of the residential area. It can be useful to better understand people' choice to engage in social activities in other parts of the city.	VERITAS-CAPI	0.54
9.	Perceived pedestrian accessibility **	The ratio of the number of types of services accessible by foot and the maximum number of types of services (12).	The perceived pedestrian accessibility of the neighborhood can be useful to understand people's choice to engage in social activities in other parts of the city.	VERITAS-CAPI	0.94
10.	Social support *	A total of six questions on a 4-point Likert scale: in my neighborhood, outside my neighborhood, no. Higher	The perceived social support in the neighborhood can be meaningful regarding people's choice to find	VERITAS-CAPI	0.17

		scores indicate higher degrees of social isolation, with scores ranging from 0 to 1.	social support in other areas of the city.		
11.	Neighborhood safety **	Perceived safety measured on a 3-point scale: high, medium, low.	Perceived safety can be a proxy for urban quality.	VERITAS-CAPI	0.46

Table 2: Residential neighborhood indicators

Social Network Indicators (* Descriptive Variables; **Analytical Variables)

Name	Indicator	Meaning	Resource	Source data	Mean

1.	Degree centrality**	The number of connections from ego to alter.	The number of social network members with whom the participant usually performs social activities. Individuals with a high degree of centrality have more influence and engage in more social activities.	(M. Newman, 2010b)	VERITAS	5.66
2.	Connectivity/network Density**	The ratio of the numbers of edges and the maximum possible numbers of edges in the network.	The percentage of possible connections vs. the effective connections among all social members.	(M. Newman, 2010b)	VERITAS	0.79
3.	Simmelian brokerage**	The role of the ego as a broker in the graph.	The extent to which the social network components are disconnected from each	(Latora et al., 2013)	VERITAS	2.44

			other when removing the participant from the network.			
4.	Global Clustering coefficient*	The ratio of the triangles and the connected triples in the graph.	The extent to which the social network components are embedded in a closed cohesive structure.	(M. Newman, 2010b)	VERITAS	0.79
5.	Diversity Index**	The Evenness Index for types of alters (husband/wife, child, other family members, friends, co-workers, acquaintances): the average number of friendships that the ego has with agents who are of the same type, and the average number of friendships that the ego forms with agents of different types.	The extent to which aged people are connected with different categories of people.	(Putnam, 1993)	VERITAS	0.49

6.	Homophily Index	The probability of having relationships with similar people for age, sex, education, and occupation.	The extent to which people with similar personal or social traits are connected.	VERITAS	Age - 0.26 Sex - 0.25 Education - 0.26 Occupation - 0.23

Table 3: Social network indicators

Mental Health Indicators (*Descriptive Variables; **Analytical Variables)					
Name	Indicator	Meaning	Reference	Source data	Mean
1. CES-D20**	A total of 20 questions on a 4-point Likert scale: Rarely or none of the time (less than 1 day); Some or a little of the time (1–2 days); Occasionally or a moderate amount of time (3–4 days); Most or all of the time (5–7 days). Range: 0–60. Individuals scoring >16 are considered to be depressed.	Depression status of the interviewed.	(Radloff, 1977)	VERITAS-CAPI	8.88
2. CASP-12**	A total of 12 questions on a 4-point Likert scale (‘often’, ‘sometimes’, ‘rarely’, ‘never’). Range: 12–48, with higher scores representing higher quality of life.	Perceived quality of life of the interviewed.	(Hyde et al., 2003)	VERITAS-CAPI	25.49
3. STAI Y-B**	A total of 20 questions on a 4-point Likert scale.	Anxiety of the interviewed.	(Spielberger et al., 1983)	VERITAS-CAPI	34.77

Table 4: Mental health indicators

	RC1	**RC2**	**RC3**	**RC4**
streng~~h~~th_direct			**0.934**	
streng~~ht~~th_all	0.182		**0.9**	0.122
network_density	-0.217	**0.953**		
Clustering coefficient	0.309	**0.878**		0.343
Simmelian brokerage	0.193	**-0.814**	0.112	0.531
assortativity_sex	**0.676**		0.184	0.331
assortativity_occupation	**0.896**	-0.127	-0.111	
assortativity_class_age	**0.81**		0.129	-0.12
res(simbrok)			0.131	**0.932**
res(clustcoeff)	**0.702**	0.254	0.169	0.543

Table 5: Loadings for each variable in each dimension of the PCA

	CES-20 (Depression)			CASP-12 (Quality of life)			Stay Y-B test (Anxiety)		
	Estimate	Z-value	P-value	Estimate	Z-value	P-value	Estimate	Z-value	P-value
Dim 1	0.15±0.36	0.42	0.670	-0.08±0.26	0.51	0.604	0.23±0.41	0.56	0.577
Dim 2	-0.30±0.35	0.86	0.389	-0.07±0.15	0.46	0.647	-0.66±0.45	1.44	0.150
Dim 3	0.78±0.46	1.66	0.096	-0.16±0.21	0.77	0.438	0.36±0.58	0.53	0.536
Dim 4	0.42±0.54	0.76	0.443	0.11±0.23	0.47	0.603	0.37±0.61	0.55	0.548
Degree	0.06±0.26	0.77	0.810	-0.08±0.11	0.72	0.469	-0.22±0.36	0.60	0.547

Table 6: Averaged statistical values following the model~~s~~ selection for the three health status as response variables and the four dimensions, plus the degree as independent variables