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Structure of personal networks and cognitive abilities: A study on a sample of Italian older adults

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Abstract

Research in social gerontology has suggested that structural complexity of personal networks could moderate cognitive decline of older adults. In line with the *environmental complexity hypothesis*, their cognitive functioning would benefit from a high number of cohesive subgroups in their own personal networks, i.e., various social *foci*, thanks to higher cognitive stimuli from various social interactions. Yet, past studies considered only compositional diversity of networks due to lack of data on alter-alter ties. To fill this gap, we collected survey ego-network data on frequent social contacts (including alter-alter ties) and cognitive functioning on a sample of individuals aged $\geq$ 75 in Brescia, Italy ($N = 230$). As a proxy for *social foci*, we detected cohesive subgroups within each respondent's personal networks. Results showed a positive association between the number of cohesive subgroups and cognitive functioning, regardless of the network size, while controlling for relevant

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socio-demographic attributes and depression symptoms. Our findings testify to the importance of granular network data in studying the link between social relationships and cognitive functioning.
Keywords: Social relationships, Cognitive functioning, Ageing, Environmental complexity hypothesis, Ego-networks

1. Introduction

Late-life cognitive decline is increasingly considered a public health issue, as it affects crucial social and economic scaffolds, such as family, local communities, and public welfare (Gauthier et al., 2021). Older adults' cognitive decline is especially important because of its high prevalence in ageing populations. The WHO has estimated that 78 million older adults will suffer from dementia or severe cognitive impairment by 2030 (World Health Organization, 2021), which is a possible consequence of accelerated cognitive decline (Petersen et al., 2001). Therefore, research on the social mechanisms that can reduce the risk of cognitive decline is key to explore a mix of social and health policies for the prevention of these cognitive diseases.

In the last two decades, research in social gerontology has considered that a higher structural embeddedness of individuals in social networks would dampen the effect of cognitive decline among older adults, thereby decreasing the risk of dementia (Wang et al., 2002; Fratiglioni et al., 2004; Wilson et al., 2007; Kuiper et al., 2015, 2016). A recent systematic review and meta-analysis has found an overall positive effect of certain aspects of social relationships on older adults' cognitive abilities, although measured through highly heterogeneous instruments (Piolatto et al., 2022). While evidence of the effect of personal networks' *size* is inconclusive (Fratiglioni et al., 2004; Holtzman et al., 2004; Ellwardt et al., 2015; Marioni et al., 2015; Ali et al., 2018; Piolatto et al., 2022), recent studies have focused on the structural "complexity" — i.e., the variety of types of relationships — of personal networks as a property that could prevent cognitive decline (Ellwardt et al., 2015; Ali et al., 2018; Piolatto et al., 2022).

This focus on the *structure* of personal networks is consistent with certain hypothetical mechanisms explaining the link between social relationships and older adults' cognition (Ellwardt et al., 2015; Piolatto et al., 2022). In line with the *environmental complexity hypothesis*, structural complexity of personal networks, rather than size, would stimulate cognition and stronger brain activation (Schooler, 1984; Hultsch et al., 1999), thereby generating better adaptation to brain atrophy and memory dysfunction in ageing (Kempermann et al., 2002; Valenzuela et al., 2012).

However, past studies have not yet fully exploited the explanatory power of structural ego-network measurements (McCarty, 2002; Bidart et al., 2018; Vacca, 2020; Maya-Jariego, 2021). Indeed, previous research has actually measured networks' compositional diversity, i.e., the number of social roles in one's personal network (Ellwardt et al., 2015; Ali et al., 2018), mostly because of the unavailability of data on alter-alter ties. It is probable that higher cognitive stimuli can rather be provided by a variety of *social foci* of an individual's activity (Feld, 1981), which can relate to the number of cohesive subgroups within one's personal network (McCarty, 2002; Vacca, 2020).

Here, we aimed to test the association between the number of cohesive subgroups in older adults' personal networks and their cognitive abilities through more granular personal-network data. We collected survey data on personal networks (including alter-alter ties), cognitive functioning, and socio-demographic properties on a sample of 230 individuals aged 75 years or older living in the city of Brescia (North-Western Italy). Our results show a positive association between the number of cohesive subgroups and cognitive abilities of older adults, regardless of network size. This corroborates the hypothesis that a variety of *social foci* of activity could protect older adults' cognitive functioning by stimulating cognitive abilities.

The remainder of the article is organised as follows. Section 2 reviews past relevant research and presents our hypothesis. Section 3 illustrates our data collection and measurements. Section 4 shows our results and Section 5 discusses our main findings and study limitations.

2. Background

Research in social gerontology and the sociology of ageing has shown that social relationships are key to dampen cognitive decline among older adults, thereby reducing the risk of dementia. A recent systematic review and meta-analysis of 61 longitudinal cohort studies published between 1989 and 2020 has shown that several aspects of older adults' social relationships are positively associated with cognitive abilities (Piolatto et al., 2022). Despite considerable heterogeneity in measurements of social relationships, a consistent positive association was found across studies analysing both structural and functional (e.g., receiving social support or avoiding feelings of loneliness) aspects of social relationships (see also Kuiper et al., 2016).

More specifically, research on structural aspects of social relationships suggests that network-related processes can facilitate older adults' access to certain functional resources, including social capital and social support (Lin, 1986; Berkman et al., 2000). In this regard, scholars have mainly focused on the role of ego's network size, i.e., the number of alters with whom ego is in frequent contact.

Yet, findings on the effect of size are inconclusive and this is mostly due to weak consensus on measurements (Piolatto et al., 2022; Kuiper et al., 2016). For instance, in a study on a sample of U.S. citizens, Ali et al. (2018) found an almost null effect of personal networks' size on cognitive abilities. However, their measurement of personal networks was limited to respondents' strong ties. Even less encouraging results were provided by Kats et al. (2016), who could not find any evidence of an effect of large vs. small personal networks in a sample of African-American and Caucasian U.S. citizens. At the same time, Marioni et al. (2015) found weak evidence of the effect of large vs. small personal networks on a sample of French older adults. Ellwardt et al. (2015) found a positive longitudinal association between the total number of frequent contacts and cognitive functioning in a sample of older adults in the Netherlands. Unfortunately, the estimated effect size was relatively small and was not adjusted for the confounding effect of alcohol consumption and depression.

Following Ellwardt et al. (2015), it is unlikely that measuring personal networks' size provides an adequate method to test the effect of the structure of social relationships on older adults' cognitive abilities. Indeed, a possible mechanism through which social relationships could dampen cognitive decline is the so-called *environmental complexity* hypothesis. This argues that brain activation could be especially promoted by a diversity of environmental stimuli, such as the coordination of multiple decision-making processes yielded by social interaction (Schooler, 1984). This would prevent cognitive atrophy by challenging cognitive abilities, as suggested by the *use-it-or-lose-it* hypothesis (Hultsch et al., 1999). Therefore, it is the diversity of social interaction contexts that can provide rich cognitive stimulation, rather than the mere size of personal networks.

Unfortunately, only a few studies have analysed the effect of personal networks on cognitive functioning beyond size. Ellwardt et al. (2015) also found a longitudinal positive association of personal networks' compositional diversity (McCarty et al., 2019) with cognitive functioning net of the confounding effect of network size. Moreover, they found that age-related cognitive decline was dampened if network diversity did not decrease over time. Compositional diversity was measured through the Cohen's Social Network Index (Cohen et al., 1997), which counted the 'social roles' represented within their respondents' personal networks (e.g., household member, friend, former colleague). By employing a similar measurement of diversity, Ali et al. (2018) found a similarly positive effect among respondents' strong ties.

However, if we consider research on the structure of personal networks (McCarty, 2002; Vacca, 2020), we can hypothesise that the cognitive stimulation of individuals cannot be entirely reflected by the compositional diversity of their personal networks. More precisely, individuals often interact across different *social foci* of activity (Feld, 1981), which are reflected in the cohesive subgroups into which their personal networks are structured (McCarty, 2002; Vacca, 2020). Depending on the social focus of an interaction, ego could be required to behave differently in various social contexts by enacting different relational schemes (Fiske, 1991). This would include, for instance, the compliance to different social norms, the adoption of different styles of communication and linguistic jargon, and the capacity of understanding different shared values, which would result into higher exposure to cognitive stimuli.

Furthermore, the position of alters in different clusters within a network does not necessarily overlap with their social roles. Suppose, for instance, that ego reports about two different alters in her/his personal network, both identified as 'neighbours'. However, while ego interacts with the former within the context of a reading club where classic books are monthly discussed, interactions with the latter mainly occur in the context of shared attendance of a local sports arena as supporters of the same football club. These two neighbours would probably be tied to two different sets of alters in the ego network, thereby forming two different cohesive subgroups, despite being identified with the same social role of 'neighbour'. This would expose ego to two different normative and cultural environments and different sources of information.

Unfortunately, none of the studies linking compositional diversity to older adults' cognitive functioning (Piolatto et al., 2022) have exploited data on alter-alter ties to test the effect of the cohesive subgroups on older adults' cognitive functioning.

Here, we hypothesised that:

The number of cohesive subgroups in personal networks is positively as-

sociated to the cognitive functioning of older adults, regardless of their own network size.

3. Methods

3.1. Data collection

To test this hypothesis, we partnered with the local municipality of Brescia (Lombardy, North-Western Italy) to conduct a personal-network survey on a sample of older adults residing in the city. Upon knowledge domain and population data on the various urban areas of the city, we selected three neighbourhoods to ensure a different socio-economic composition of the sample: the city centre, Villaggio Prealpino (in the Northern suburbs), and Villaggio Sereno (in the Southern suburbs).

We sampled the target population in two steps. First, we drew a random sample of 851 individuals from the entire list of the target population, which included 4,248 individuals aged 75 years or older. The sampling frame was provided by the administration of the Brescia municipality on 26 October, 2018. 107 of the selected individuals agreed to participate to the study (12.5% response rate). To increase the sample size, we recruited an additional convenience sample of 123 individuals with the help of local civic organisations involved in the project, which resulted in a total sample size of $N = 230$ respondents (more detail on the differences between the probabilistic and non-probabilistic sub-samples is reported in the Supplementary Material, Section S1).

A team of six native-speaking trained interviewers personally administered a questionnaire in 2019 to 194 respondents, while the remaining 36 interviews were conducted over the telephone at the outset of the local Covid-19 epidemic in early 2020. The questionnaire was administered in Italian and all respondents were native speakers.

3.2. Variables and Measurements

3.2.1. Cognitive functioning

We assessed the respondents' cognitive functioning through the Italian version of the Mini-Mental State Examination (MMSE), a 0-30 global score largely used to screen older adults' cognitive abilities. It was calculated by counting correct outcomes of 11 tasks designed to assess respondents' abilities on spatio-temporal orientation, memory, attention, basic calculation, and language (Folstein et al., 1975; Measso et al., 1993). In case of telephone interviews, we used the Itel-MMSE, i.e., a special version of the Italian MMSE validated for telephone interviews (Metitieri et al. 2001; see also Roccaforte et al. 1992; Martin-Khan et al. 2010). We then re-coded the Itel-MMSE scores to the MMSE scale to ensure full comparability. As reported in the Supplementary Material (Section S2), we found no qualitative difference between the whole sample (face-to-face + telephone) and the sub-sample including only face-to-face interviews.

3.2.2. Personal networks

We collected data on the respondents' personal networks through an 8-item name generator (Perry et al., 2018). This included various questions to elicit names of the respondents' frequent contacts in different sociability contexts, including: i) the subject's household; ii) households of any adult children not co-residing; iii) other relatives; iv) neighbours; v) current or former co-workers; vi) co-members of civic organisations, e.g., churches, volunteering, or political associations; vii) other friends or acquaintances; viii) other contacts. Name generators were designed to capture personal contacts with whom the respondent interacted frequently and whom were perceived as "important" (van Tilburg, 1998; Ellwardt et al., 2015). We limited the potential alters to a fixed *maximum* number of 29 to keep personal networks homogeneous across respondents in terms of perceived importance of their mentioned contacts. Moreover, we collected data on alter-alter ties through edge interpreters, by asking respondents to report about possible acquaintance between their cited contacts, i.e., whether they would interact with each other independently from ego in case they had such opportunity (note that an English translation of the name generators is reported in the Appendix).

Cohesive subgroups: We calculated the number of cohesive sub-graphs — i.e., subsets of the personal networks' nodes showing high connectedness to each other and low connectedness to other nodes (Wasserman and Faust, 1994) — through the Girvan-Newman algorithm (Newman and Girvan, 2004). We selected this algorithm because it maximised modularity, i.e., the ratio between the number of edges within detected sub-graphs and the number of edges between them (see Fortunato and Hric, 2016, for a review). This method is ideal for relatively small networks as our respondents' personal networks (see also Vacca, 2020). To test its reliability, we calculated the number of sub-graphs through the Louvain algorithm (Blondel et al., 2008), which yielded similar results. We performed these calculations through the algorithms implemented in the *R igraph* package (R Core Team, 2021; Csardi and Nepusz, 2006).

Network size: We calculated the number of alters for each subject. Note that this variable was censored by design at 29, as explained above.

3.2.3. Socio-demographic characteristics

We collected information on certain socio-demographic characteristics through the questionnaire and secondary data provided by the local municipality.

Age was calculated based on the distance between the respondents' date of birth (previously provided by the local municipality upon a data protection agreement) with the interview date.

Education was measured through a 5-level scale (i.e., primary school, lower secondary school, upper secondary school, graduate degree, post-graduate degree) and then re-coded into a 4-level categorical variable by merging levels 4 and 5, because of the latter's low frequency.

Gender was measured through a 3-item question (i.e., male, female, other) and then re-coded into a binary variable as none of the respondents had selected the latter option.

Depression symptoms were measured through a binary variable accounting for those respondents who reported values greater than 1 on the Italian version of the 5-item Geriatric Depression Scale (GDS; Rinaldi et al. 2003), as opposed to those who did not.

Finally, we built a binary variable on whether respondents were residing in an *assisted living facility*.

Missing values were imputed through multiple imputation by chained equations via the *mice* (van Buuren and Groothuis-Oudshoorn, 2011) package in R (R Core Team, 2021).

4. Results

4.1. Descriptive Results

Figure 1 shows the distribution of *cognitive functioning* (MMSE) in our sample. The distribution was highly negatively skewed, with 27.00 as the median value in a 0-30 range ($IQR = 3.64$).

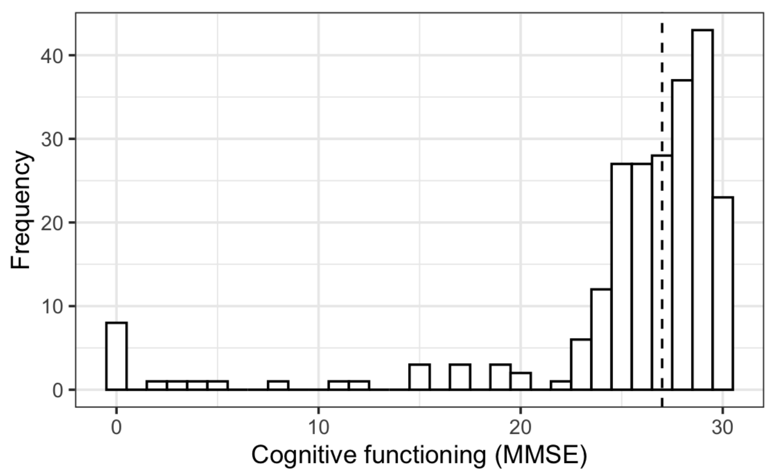


Figure 1: Distribution of *cognitive functioning* (MMSE) of the respondents. The dashed line represents the median value.

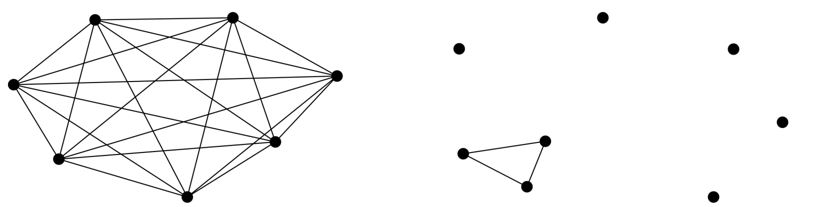
Table 1 summarises the central tendency and dispersion values of our variables. The number of *cohesive subgroups* in respondents' network structure showed a right-skewed distribution between 0 and 10, with 37.83% of respondents' networks below the median value of 3 ($IQR = 2$), with an average size of 11.98 ($SD = 6.63$). Figure 2 shows four examples of respondents' personal networks, with varying levels of *network size* and *cohesive subgroups*.

The distributions of *cohesive subgroups* and *network size* are reported in the Supplementary Material (Section S1).

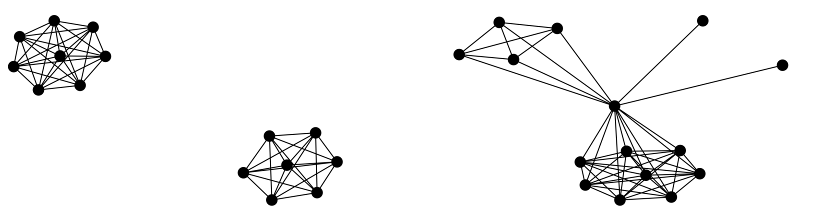
	Central tendency (dispersion)	Range
Cognitive functioning (MMSE)	$Mdn = 27.00$ ($IQR = 3.64$)	0-30
Cohesive subgroups	$Mdn = 3$ ($IQR = 2$)	0-10
Network size	$M = 11.98$ ($SD = 6.63$)	0-29
Age	$Mdn = 81$ ($IQR = 8$)	75-100
	Proportion (%)	
Gender		
women	56.09	
men	43.91	
Education		
primary	33.04	
lower secondary	24.78	
upper secondary	26.52	
tertiary	15.65	
Assisted living facility	15.65	
Depression symptoms (GDS $>$ 1)	20.00	
Number of respondents	230	

Table 1: Descriptive statistics.

In terms of socio-demographic characteristics, our respondents' age ranged between 75 (by research design) and 100, with 46.09% of the respondents below the median age (81, $IQR = 8$). Unfortunately, the sample was imbalanced towards women (56.09%) and higher levels of education compared to the general population (e.g., 42.17% of respondents had obtained at least an upper secondary school degree). As regards respondents' mental health, 20.00% reported depression symptoms, according to the GDS scale. Finally, 15.65% of the respondents were residing in assisted living facilities.



(a) Ego 41, *size* = 7, *subgroups* = 1 (b) Ego 214, *size* = 8, *subgroups* = 6



(c) Ego 42, *size* = 15, *subgroups* = 2 (d) Ego 54, *size* = 15, *subgroups* = 5

Figure 2: Four examples from the respondents' personal networks with varying levels of network *size* and *cohesive subgroups*.

4.2. Multivariate Analysis

To test our hypothesis, we estimated a linear regression model of *cognitive functioning* as a function of the number of *cohesive subgroups*, by assuming *network size* as a confounding factor. We adjusted the model for various socio-demographic confounding factors (*age*, *gender*, and *education*), *depression symptoms* (GDS > 1) and residing in an *assisted living facility*. Figure 3 shows the estimated coefficients of *cohesive subgroups* and *network size*. We considered 95% confidence intervals according to Huber-White standard errors, which are robust to heteroskedasticity.

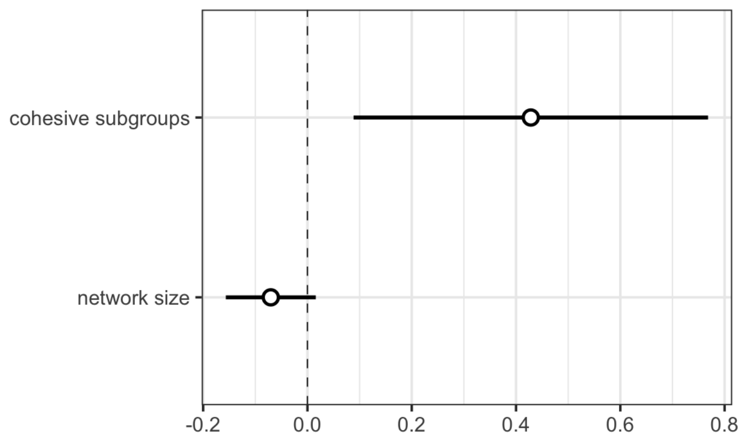


Figure 3: Estimated coefficients of *cohesive subgroups* and *network size* as linear predictors of *cognitive functioning* (MMSE): OLS point estimates and 95% confidence intervals based on Huber-White standard errors. Model adjusted for *age*, *gender*, *education*, and *assisted living facility* ($n = 230$). Full results in Table 2.

Figure 3 shows a positive association of *cohesive subgroups* with *cognitive functioning* ($\hat{\beta} = 0.43$, 95% CI [0.07, 0.79]), adjusted for the confounding effect of *network size*, depression symptoms and the socio-demographic characteristics included in the model. More precisely, our results indicate that an increase by one cohesive subgroup in a respondent's personal network determined on average a MMSE increase of a value ranging between 0.07 and 0.79 at a 95% confidence level, all other factors being equal. This result would confirm our hypothesis. Table 2 reports all coefficients of the estimated model.

	Coefficients	Robust SE	95% CI	p
cohesive subgroups	0.43	0.18	[0.07, 0.79]	0.020
network size	-0.07	0.05	[-0.16, 0.02]	0.131
age	0.04	0.09	[-0.13, 0.22]	0.623
gender (male)	-0.48	0.71	[-1.88, 0.91]	0.496
education				
lower secondary	2.30	0.99	[0.35, 4.25]	0.021
upper secondary	1.74	0.89	[-0.01, 3.49]	0.051
tertiary	1.70	1.04	[-0.35, 3.75]	0.104
depression symptoms (GDS > 1)	-2.35	1.26	[-4.83, 0.13]	0.063
assisted living facility	-10.62	1.96	[-14.49, -6.76]	<0.001
(constant)	22.17	7.41	[7.56, 36.77]	0.003
N. observations		230		
R^2		0.436		

Table 2: Linear regression model of *cognitive functioning* (MMSE) with point estimates, Huber-White standard errors, 95% confidence intervals, and p-values. Reference categories: "female" for *gender*; "primary school" for *education*; "no" for *depression symptoms* and *assisted living facility*.

5. Conclusions and Discussion

In this study, we analysed the relationship between the number of cohesive subgroups in older adults' personal networks and their cognitive functioning. By following Ellwardt et al. (2015), we hypothesised that higher structural complexity in personal networks could improve cognitive functioning of older adults via higher cognitive stimuli (Schooler, 1984; Hultsch et al., 1999).

Using a sample of older adults in Brescia, Italy, we found a positive association between the number of cohesive subgroups within respondents' personal networks and their cognitive functioning. This relationship was confirmed by controlling for the confounding effects of personal networks' size, respondents' depression symptoms and other individual socio-demographic properties.

Unlike previous studies (Ellwardt et al., 2015; Ali et al., 2018), we assumed that the number of cohesive subgroups rather than compositional diversity could be a more appropriate measure of networks' structural aspects responsible for higher cognitive stimuli, as they would relate to different social *foci* of activity (Feld, 1981). This was possible by collecting more granular personal network data, including alter-alter ties. To the best of our knowledge, this is the first study on the link between social relationships and cognitive functioning that relies on such type of network data (Piolatto et al., 2022). Yet, structural measures are key to test the effect of social relationships on cognitive functioning via cognitive stimulation.

This said, our study has various limitations, mainly due to our sample. First, by relying on cross-sectional data, we could not assess any causal effect, as only longitudinal data would allow us to rule out any reverse causality effect between social relationships and cognitive functioning. Second, we could not rely on a fully probabilistic sample. These aspects limit the generalisability of our results. However, note that both limitations are mainly due to the practical difficulties of collecting older adults' personal-network data including alter-alter ties, which is hardly feasible with larger, longitudinal surveys, which in turn would be ideal to avoid reverse causality and increase generalisability. Indeed, collecting personal-network data of older adults is particularly challenging as face-to-face questionnaire administration is hardly replaceable by computer-assisted techniques without compromising measurement accuracy. Although recent studies suggest that there is no difference in network recalling ability among older adults with mild cognitive impairment (Roth et al., 2021), more research is needed to develop reliable and efficient data collection strategies for older adults' personal networks.

Furthermore, future research on the link between social relationships and cognitive functioning should consider new data collection strategies for gathering such personal-network data in large-scale panel studies, including alter-alter ties (e.g. Cornwell et al., 2020; Stulp, 2021; Tulin et al., 2021). This would permit us to improve our understanding of causal effects between social relationships and cognitive functioning of older adults by overcoming the trade-off between powerful research designs (e.g., longitudinal cohort studies on large-scale representative samples without rich network data) and appropriate measurement of personal-network data, which are considerably more burdensome (McCarty et al., 2007; Stadel and Stulp, 2022; Peng et al., 2023).

Appendix A. Name generators

Each of the following questions were used by the interviewers to elicit alters' names from our respondents, in case alters were above 18 years of age.

1. Who are the members of your household? Please state their names.
2. Have you got any offspring not residing with you? Please state their names.

3. Are your offspring married or do they live with a partner? If so, please state your offspring's spouses' or partners' names.
4. Is there anyone else among your relatives whom you consider important and with whom you have frequent contacts? Please state their names.
5. Are there any neighbours or people living in the neighbourhood, whom you consider important and with whom you have frequent contacts? Please state their names.
6. Are there any (former) co-workers or colleagues whom you consider important and with whom you have frequent contacts? Please state their names.
7. Do you participate to any association, community organisation (including political parties, trade unions, voluntary organisations) or church? If so, is there anybody in these organisations whom you consider important and with whom you have frequent contacts? Please state their names.
8. Are there any other friends or acquaintances whom you consider important and with whom you have frequent contacts? Please state their names.
9. Is there anybody else whom you consider important and with whom you have frequent contacts? Please state their names.

For each unordered pair of cited alters (i, j), the following question was then asked: "Does i know j? In case he/she had the opportunity, would i interact with j even in your absence?"

Appendix B. Ethical approval

The study design was approved by the Ethics Committee of the University of Brescia, Italy, on 31 July 2018.

Appendix C. Supplementary material

Supplementary material related to this article can be found online at `https://doi.org/10.1016/j.socnet.2023.02.005`.

Appendix D. Data availability

The dataset for replication is available at `https://doi.org/10.7910/DVN/XXLBSI`.

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Appendix G. Declaration of competing interest

The authors declare that they have no known competing finan-cial interests or personal relationships that could have appeared toinfluence the work reported in this paper.

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