Mapping protective performance of social network types on health and quality of life in older people in European regions

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Abstract

Objectives: To identify social network profiles using Latent Profile Analysis (LPA), to study the relationships of these profiles with health markers, mental health, quality of life, and cognitive functioning, and to compare profiles across European regions. **Methods:** 27,272 participants from the Wave 8 of the SHARE project, aged 65 or older (M= 74.95, SD=7.17) from Europe. Statistical analyses included LPAs followed by MANOVAs to compare the profiles and the health markers. **Results:** Five profiles were identified: family, friends, spouse, diverse, and others. A no network group was also added. The prevalence of the specific profiles differed across European regions. Individuals with no network and those categorized into the others profile presented the worst health outcomes. **Discussion**: The "friends" network is more protective toward cognitive functioning and physical health and the "spouse" and "family" ones are more protective toward mental health. The variability according to European regions is discussed.

Keywords: social network typologies; health; older adults; SHARE; Latent Profile Analysis

Introduction

The term social network could be defined as a group of close people that provide companionship, advice, help, or care (Ye & Zhang, 2019). Social networks are fundamental drivers in our lives, and their connections with health, well-being, and quality of life are essential, especially in older age (Litwin et al., 2020) when the need for social support increases (Wrzus et al., 2013). Wenger (1996) was one of the first authors to study social network typologies in the gerontological context, distinguishing five social network types in older people in the UK. Litwin enhanced and broadened the research in this field with multiple studies and improved the research method by using data from the social network module of the SHARE project. Litwin and colleagues followed the "confidant approach", which focuses on the respondent's most meaningful relationships instead of analyzing the whole social network. In addition to these pioneering studies in the field, interest in social network typologies has grown and we can find several recent studies such as the ones from Cohn-Schwartz et al. (2021) or Lestari et al. (2022).

Even though these studies used different criterion variables, they usually followed the theoretical framework of the Convoy model of social relationships of Antonucci et al. (2014), and included the social network's main aspects as variables. These aspects were defined by the following model: the structure (e.g., network size and composition), the interactions or dynamics with network members (e.g., frequency of contact) and the quality of the relationship, and the feeling of closeness with those who are part of the network (Ye & Zhang, 2019). There has not yet been any consensus regarding the number of typologies or their composition (Harasemiw et al., 2019) but there are four types of networks that stand out in most studies: A "diverse" network (that includes relationships with family, neighbors, and friends), the "family" network (based primarily on close ties with family members such as spouse, children, and siblings), the "friends" network (primary composed of friends), and the "restricted" network or "no network" that only have minimal or no ties, respectively (Cheng, 2009; Fiori et al., 2008; Litwin et al., 2021). This no network type is composed, in some studies such as the one by Litwin and Stoeckel (2014), of all those who claim to have no one in their confidant network.

In most studies, the methodology used to determine the number of types is cluster analysis. However, recent research has been using mixture analyses such as latent class (LCA) or latent profile analysis (LPA) (Cohn-Schwartz et al., 2021; Harasemiw et al., 2019; Lestari et al., 2022; Park et al., 2018a). Mixture analysis is used to classify unobserved subpopulations with a series of indicators but has some differences compared to traditional cluster analysis (Magidson & Vermunt, 2002). It can use combinations of categorical and continuous variables, has statistical and model fit indices to identify the best fitting number of types (Bergman & Magnusson, 1997; Steinley, 2003), and avoids biased results caused by different variances of the clustering variables (Ketchen & Shook, 1996). For this reason, the present study aims to replicate the classification of Litwin and Stoeckel (2014) using this analytical tool.

The literature has consistently shown that older people with diverse and close social networks report better subjective well-being (Fiori et al., 2006; Li & Zhang, 2015; Litwin & Stoeckel, 2014), better life satisfaction (Cheng et al., 2009; Harasemiw et al., 2019), less loneliness (Litwin & Shiovitz-Ezra, 2011) and depression (Cheng et al., 2009; Fiori et al., 2006; Harasemiw et al., 2019; Park et al., 2018a; Ye & Zhang, 2019), better physical health (Fiori et al., 2006; Park et al., 2018a, Ye & Zhang, 2019), and better cognitive functioning (Cohn-Schwartz et al., 2021; Lau et al., 2019), while those with restricted networks present the worst health outcomes. However, social network groups with intermediate structures show less consistent results (Harasemiw et al., 2019). For example, there are inconsistencies regarding the family and the friendship network, with contrasting results when it comes to which network has better outcomes. Some studies have highlighted that the family network has better life satisfaction outcomes and less depression than the friendship network (Cheng et al., 2009), and others have revealed that a friendship network is more protective toward depressive symptoms than the family network (Fiori et al., 2006; Park et al., 2017).

A possible explanation for these somehow contradictory results could lie in the cultural context, and the differences regarding the societal structures of social interactions and relationships. Therefore, some types of networks may be linked to culture (Cheng et al., 2009; Fiori et al., 2006) and the relationships between health variables and typologies may differ according to cultural context (Ye & Zhang, 2019). For example, in the study by Fiori et al. (2008), social network types were related to the physical and mental health of older adults in the United States, but they did not find this relationship in the sample from Japan. Differences have also been found among European countries, for example, Litwin and Stoeckel (2014), found that, in general, southern countries had a higher prevalence of proximal family network types compared to northern and western countries. Therefore, agreement has not yet been reached on the empirical relationship between social network types and health, and to study this relationship, the cultural context in which these networks are established must be examined.

In summary, even though the classification of older people into social network typologies has been analyzed in several studies, there is a lack of consensus regarding the number of types, their definition, and the criterion variables. Moreover, even though the literature supports the relationship between social network typologies and mental and physical health, all these health measures have not been simultaneously approached while studying potential cultural differences. This cultural perspective could give a broader view of the relationships between social network types and health (physical and mental) during old age.

The objective of this study is to broaden the knowledge of this field by identifying the social network typologies through latent profile analyses, studying the network characteristics and their relationships with health indicators, and comparing groups according to European regions to identify possible cultural differences.

Method

Data and Participants

This study was based on data from the 8th wave of SHARE (The Survey of Ageing and Retirement). The respondents of the SHARE project are people aged 50 and older from 28 European countries and Israel. In addition, current partners living in the same household are interviewed regardless of their age. It presents a longitudinal design and a probability-based sampling. The data for this wave was collected in 2019 and 2020, and offers the most recent gathered data. More information about the SHARE survey design is available (see Börsch-Supan, 2022; Börsch-Supan et al., 2013).

Regarding the sample for this study, we included a subsample of 27,272 individuals, aged between 65 and 102 (M= 74.95, DT=7.17) to focus on the older population, from which 12,050 (44.2%) were males and 15,222 (55.8%) were females. Most of them were married (62.9 %), some were widowed (23.2 %) or divorced (7.6 %), and the rest (6.3%) presented another marital status. For the purposes of this study, we established the division of 20 European countries into four regions according to recent SHARE studies: northern Europe (Denmark and Sweden), western Europe (Austria, Germany, France, the Netherlands, Switzerland, Belgium, Ireland, and Luxembourg), southern Europe (Spain, Italy, Greece and Portugal), and eastern Europe (Czech

Republic, Poland, Hungary, Slovenia, Estonia and Croatia) (Ahrenfeldt et al., 2018; Horackova et al., 2019). Although these regions are mainly defined geographically, they are also defined by the typology of European welfare regimes, cultural and contextual factors, and individual behaviors of older adults (Lakomy, 2020).

Instruments

Social network

SHARE includes a social network module in which participants can list a maximum of 7 people with whom they usually discuss important things. Additional information is requested about all the people listed in the network. The participants that do not name anyone are classified into the “no network” group.

The criteria or indicators for the latent profile analyses were part of the social network module, we chose the same eight variables used by Litwin and Stoeckel (2014), the number of people in that category divided by the size of the network (e.g., if you only have two people in your network and one is your partner or spouse, they would make up 50% of your network), that is, the proportion of the named network composed of the following relationship groupings: (a) spouse or partner, (b) children, (c) other relatives (parents, in-laws, siblings, grandchildren, or extended family), (d) friends, (e) others (neighbors, (former) colleagues, or formal helpers), (f) close proximity (proportion who reside within 5 km of the respondent, the original response categories were <1, 1–5, 5–25, 25–100, 100–500, and >500 km), (g) daily contact (proportion of named confidants contacted daily, the survey response categories were daily, several times a week, about once a week, about every 2 weeks, about once a month, and less than once a month), and (h) emotional closeness (proportion of cited people in these categories, original survey categories were not very close, somewhat close, very close, and extremely close).

Other variables

Health status was assessed using the self-perceived health indicator "Would you say your health is...?" ranging from 1 (poor) to 5 (excellent) (Ware & Gandek, 1998) and the number of chronic diseases were considered. Subjective well-being was evaluated with the indicator "How satisfied are you with your life?" ranging from 0 (completely dissatisfied) to 10 (completely satisfied) and the CASP scale, a 12-item version that ranges from 12 to 48, (Hyde et al., 2003), composed of 4 domains: control, autonomy, self-fulfillment, and pleasure, and that showed adequate internal consistency estimates for the total scale α =.83, ω =.83. To assess mental health, the Three-Item Loneliness Scale (Hughes et al., 2004) was employed. It contains the frequency of feeling a lack of companionship, exclusion, and isolation, with a maximum score of 9 and consistency estimates of α =.76, and ω = .76 for this sample. The EURO-D scale (Prince et al., 1999) was used to assess 12 different symptoms of depression, it can be used either as a general factor or as two factors (Affective Suffering and Lack of Motivation). For this analysis the total scale was used, which showed adequate internal consistencies α =.71, ω = .72. Finally, for cognitive functioning we employed a measure of verbal fluency, the number of correct named animals in one minute (Ardila et al., 2006), and a measure of memory using the 10-words immediate and delayed recall test (Brandt et al., 1988).

Network satisfaction was analyzed with the network satisfaction scale. This scale consists of a single question which is answered with a scale ranging from 0 (completely dissatisfied) to 10 (completely satisfied): "How satisfied are you with the relationships you have with the people we just talked about?" for people with a social network and "You indicated that there is no one with whom you discuss important matters. To what extent are you satisfied with this situation?" for people without a network.

In addition, we analyzed background characteristics for each profile such as respondents' gender, age, years of education, and economic situation.

Statistical analyses

The statistical analyses were carried out in several steps. First, considering the quantitative nature of the criterion variables, confidant network typologies were estimated employing Latent Profile Analysis (LPA) using Mplus 8.7 (Muthén & Muthén, 1998-2017).

Second, to determine the optimal number of profiles, we tested the best model fit comparing one to six groups with the Lo, Mendell, and Rubin (LMR) (Lo et al., 2001) and boot-strapped likelihood ratio (BLR) tests (McLachlan & Peel, 2000) in which statistical significance indicates an improvement when a type is added to the model. We also compared the Akaike Information Criterion (AIC), Bayesian Information Criteria (BIC), and sample-size-adjusted BIC (SSA-BIC); the lower these indices the better the model (Lin & Dayton, 1997; Wang & Wang, 2012). Additionally, Entropy values of .80 or higher evidence that the classification in the model occurs with minimal uncertainty (Tein et al., 2013). In addition to the statistical criteria mentioned above, the selection of the number of profiles is subjective and requires a theoretical justification, so the background characteristics of each type were analyzed for the retained model. We employed chi-square tests and V of Cramer effect sizes to compare categorical variables and an Analysis of Variance (ANOVA) and partial eta-squares effect sizes for the quantitative variables.

Once the optimal number of profiles was determined, we compared the physical and mental health status of the different typologies by conducting a series of Multivariate Analyses of Variance (MANOVA). The MANOVA test is used to find differences in means on multiple dependent variables, considering various categories of independent variables. To test for effects, the Pillai criterion was employed, as it is the most robust in terms of assumption violations (Tabachnick & Fidell, 2007). When the overall F-test showed differences between groups, post-hoc tests were conducted to examine which means differed significantly from others. All these additional statistical analyses were performed using SPSS 26 and JASP 0.16.

Results

Latent profile analyses

To determine the optimal number of latent profiles, we tested six models and compared the indices that are presented in Table 1. The decrease of the AIC and BIC indices and the increase of Entropy suggests that the model provided a better fit each time a profile was added. Although the p-value of the LMR and BLMR statistical model comparison suggested that a six-profile model was a significant improvement, the solution provided two very closely related groups when analyzing the six-profile model. Furthermore, these two profiles had similar patterns and represented a very low percentage of the sample indicating that they may be spurious. In an LPA it is essential to ensure that the final model and underlying profiles represent interpretable and meaningful groupings of individuals within the context of previous research, so the retained model must be supported theoretically and the discovered profiles must be interpretable (Marsh et al., 2009; Masyn, 2013). For this reason, we decided to retain the five-profile model for use in subsequent analyses, as it was the second best fit and the groups had clear differentiated patterns. The five typologies of social networks had substantial probabilities for the most likely latent type memberships (profile one=1.000; profile two=.986; profile three=.943; profile four=.983; and profile five=.996).

INSERT TABLE 1

In the subsequent analyses, we also decided to analyze the results of the “no network” profile, composed of all those without a social confidant network. Although added after the cluster analyses, the identification of individuals with this type of network is important because of their very vulnerable situation (Litwin & Levinsky, 2021). Table 2 helps interpret the five profile solution, showing the percentages of the criterion variables and the means of the network size for all respondents with at least one confidant. Two groups that emerged are family-based. The group labeled "family” was the largest in the sample and was composed mainly of the children, spouse, and other relatives, characterized by medium residence proximity, daily contact, and high emotional closeness. The type labeled "spouse" was composed primarily of the respondent’s wife or husband, was the one with the highest proximity, contact, and emotional closeness but the network size was restricted to one person. The "diverse" profile showed a varied network composition and had the largest social network size of confidants, but the proximity was moderate and contact and emotional closeness was lower when compared to the family-based profiles. The two non-family networks were labeled as "others" and "friends". The “friends” network represented a large amount of the sample and consisted mainly of friends. Compared to the other groups, emotional closeness was relatively good but there was less contact. Proximity and daily contact of the “others” network was higher than the “friends” and “diverse” profiles but it was the profile with the lowest emotional closeness.

INSERT TABLE 2

Relationships of the latent profiles with socio-demographic and health variables

Table 3 presents the background characteristics of each typology. The profiles differ in terms of gender frequencies $\chi^2(5)$ =1104.83; p<.001; V= .201, and the proportion of individuals who live with their partner $\chi^2(10)$ =2618.80, p<.001; V=.078, with women being less prevalent in the “spouse” network and people living with their partner representing lower proportions in the “others” and “no network” profiles. The profiles also differ in terms of the mean age (F (5, 27266) =132.11; p<.001; η^2=.024), the average years of education (F (5, 25625) = 93.57; p<.001; η^2=.018), the household ability to make ends meet (F (5, 18475) =49.36; p<.001; η^2=.013), and the social network satisfaction (F (5, 26665) =742.77; p<.001; η^2=.120). In all these variables, the “no network” group has the most vulnerable socio-demographic results followed by the “others” network, given that they are older, have fewer years of high school education, and less economic solvency.

INSERT TABLE 3

Table 4 provides information about the mean differences between one network typology and another for all the variables. Pillai’s trace and its corresponding F-test in the MANOVA showed that there were statistically significant differences (p<.001) between profiles in all the groups of variables for health status (F(10, 54352) =85.01; η^2=.015), subjective well-being (F(10, 50698) =58.33; η^2=.011), mental health (F(10, 51970) = 44.77; η^2=.009), and cognitive functioning (F(10, 52366) =1.85; η^2=.013). Table 4 contains information on the effect of each variable separately, revealing that belonging to one or another profile was statistically significant for all variables.

It is worth noting that overall, the “no network” group presents worse health outcomes in all variables, followed by the “others” group. The “friends” and family-based (“family” and “spouse”) groups showed good results, followed by the "diverse" group, but the results among these profiles are mixed, with no profile outperforming the rest in all variables.

In the post-hoc comparisons we can observe that the “diverse” profile had worse outcomes in chronic diseases and depression than the “family”, “spouse”, and “friends” profiles. In addition, the “diverse” profile reported higher loneliness than the “spouse” and “friends” profiles and worse results in perceived health, quality of life, memory, and fluency than the “friends” network. However, the “diverse” network showed a higher mean verbal fluency than “family” and “spouse”, and presented no differences with either in terms of life satisfaction. Detailed observations of the post-hoc tests for the “family” and “spouse” profiles revealed that most of their results are similar, but the “family” profile seems to have worse results given that the chronic diseases, loneliness, and depression means were higher than in the “spouse” profile. Regarding the post-hoc comparisons of the family-based profiles with the “friends” network, it appears that the “friends” profile has significantly fewer chronic diseases than the “family” profile and better perceived health, quality of life, memory, and verbal fluency than the "family" and “spouse” networks. However, it showed higher loneliness and depressive symptomatology than the "spouse" group.

INSERT TABLE 4

Relationships of European regions with latent profiles and outcomes.

Furthermore, the proportions of social network typologies according to European regions were examined in Table 5, observing that they differ significantly $\chi^2(15) = 1215.52$; $p<.001$; $V=.122$. The adjusted standardized residuals (ASRs) are the sum of all squared standardized residuals in the chi-squared obtained value (Sharpe, 2015), and are useful to determine which specific observed values differed more from those expected (Agresti, 2007). ASR absolute values greater than 3 were interpreted as a significant difference. Higher than expected proportions were found in the southern and eastern countries for “family” and “spouse” networks and lower for the “friends” one, the opposite was true for the northern and western countries. In addition, the “diverse” network had more people than expected in the northern and western regions and fewer in the southern region. The “others” network was more frequent in the eastern countries and less in the southern ones. As for the individuals with no network, there was a higher proportion than expected in the southern region and lower in the northern and western regions.

INSERT TABLE 5

Regarding the MANOVAs with interaction effects of cross-network typologies with European regions, we found that Pillai’s trace and its corresponding F-tests were statistically significant for all analyses: health status (F (30, 54316) =2. 24; p<.001; η^2=.001), subjective well-being (F (30, 50662) =2.39; p<.001; η^2=.001), mental health (F (30,51932) =3.40; p<.001; η^2=.002), and cognitive functioning (F (30, 52330) =1.85; p<.001; η^2=.001). However, in the inter-subject tests, some of the variables were not statistically significant, as shown in Table 6, so our interpretation of the cross-effects analyses focused on the number of chronic diseases, quality of life, depression, loneliness, and memory.

INSERT TABLE 6

In general, some trends are still observed, “no network” and “others” remained as the groups with the worst outcomes in all variables and “friends”, “family”, and “spouse” profiles had the best results in all the European regions. However, each region presented some particularities. For example, the differences between typologies in the northern region were not so pronounced and the post-hoc tests showed that differences in quality of life, loneliness, and depression only appeared when comparing all groups with the “no network” group. Although in general the “friends” group obtained better results than the “family” profile, this relationship was reversed for the western countries where the “family” and “spouse” groups showed less loneliness and depression. In the southern region, no significant differences were found between the “no network”, “others”, and “diverse” groups for most variables, showing that all these groups have deteriorated health in this region. The groups that showed better results in terms of chronic diseases, quality of life, and memory were “friends” and “spouse” equally. However, the “spouse” group showed less loneliness and depression than the “friends” group. In the eastern region, “spouse” emerged as the group with better results than “friends” and “family”, followed by the “diverse” network.

In addition, the main effects of European regions on all health variables (not shown in Table 6) were statistically significant $p<.001$ for all the analysis, the general trend was better results for the northern region, followed by the countries of the western region, and worse results for the eastern and southern regions.

Discussion

This study recognized five network types labeled “family”, “friends”, “spouse”, “diverse”, and “others”, similar to those emerging in previous research (Litwin, 2001; Park et al., 2018a; Ye & Zhang, 2019). We used the same criterion variables as Litwin & Stoeckel (2014) and the types of “friends”, “spouse”, “others” were found, but in our study, there was only one family type that consisted of a large proportion of children and other relatives instead of two separate types.

Similar to previous research, we found the “diverse” profile with a varied network structure and large network size. Research usually indicates that individuals with a diverse network of confidants have better health outcomes. However, our study showed that this profile presented overall worse outcomes than the “friends”, “family”, and “spouse” groups. This may be because in most studies the “diverse” network is also characterized by frequent participation in organizational activities (e.g., church and clubs) (Cheng et al., 2009), whereas in our research this variable was not used as a criterion. Another possible explanation is that the “others” variable includes caregivers. A higher proportion of these people in one’s confidant network may indicate that the person presents health problems that need professional care (for example, in our research the diverse group showed higher chronic diseases means than the “friends”, “family”, and “spouse” profiles).

Most individuals were classified into the "family" network and a large percentage into the "spouse" network, this is consistent with research that found that most older people can be classified into family-based networks (Fiori et al., 2008; Litwin & Stoeckel, 2014). The “others” profile represented the smallest percentage of the sample. However, a small percentage of a large sample includes enough individuals to support generalization (Vincent & Weir, 2012). Regarding the typology proportions in the different European regions, we found higher proportions of the “spouse” and “family” networks in the countries from the southern and eastern regions, and a higher prevalence of the “friends” network in the northern and western countries, similar to what other research has found (Litwin & Stoeckel, 2014). It should also be noted that in the southern region there was a higher proportion of people without a social network, which is of concern considering that these countries place great importance on both close and distant family ties (Fiori et al, 2008).

Regarding the protective role of family and friends in social networks, previous research has discussed whether friendship groups have better health outcomes than family-based groups. By studying a broad set of health variables, one of our contributions to this topic is finding that different types of social network profiles are protected differently. The friendship group has higher quality of life and cognitive functioning than family-based groups, but there are no differences in the loneliness and depressive symptomatology for the “family” and “friends” profiles and the “spouse” group is more protective. These results are in line with the argument that the friendship network is often more protective because it is self-chosen, whereas the family network is only protective if a close relationship is maintained (Fiori et al., 2008). Given that the “spouse” profile is the one that presents more emotional closeness, followed by the “family” network, these groups are protected from feeling alone. Another aspect to consider when interpreting the results according to the different profiles, is that age could be a confounding factor that could partially explain the worse outcomes in the “no network” group. As we age, the likelihood of experiencing risk factors for social isolation increases, such as living alone, retirement, loss of family and friends, or having chronic illnesses (Salma et al., 2018), so it is not surprising that the group without a network is showing the worst background and poorer health outcomes.

Some of the strengths of this study are the large sample size, the methodology employed, and the exhaustive description of variables considering the differences of each region. However, one of the main limitations is its cross-sectional nature that does not allow studying the potential reciprocal effect between health and social network typologies.

Although the literature has mostly focused on the effects of social support networks on health, it is true that worse health outcomes may also be related to a deterioration of the social network. For example, experiencing changes in health, such as suffering a stroke, has been linked to losing contact with friends and the wider social network (Northcott et al., 2018). Future longitudinal research should further investigate how changes in health and social networks are related. In this direction, some longitudinal research shows that social networks can change in old age, and it is possible to move from a less supportive social network to a more supportive one which has beneficial health effects (Litwin and Levinsky, 2021). It is important for future research to study how this shift occurs to reduce the number of older people in the “no network” group, bearing in mind that in some countries such as southern Europe the prevalence of this group is much higher than in other regions. Moreover, these studies are particularly relevant after the Covid-19 pandemic, given that many people have seen a reduction in their confidant network after the confinements and social restrictions (Mendez-Lopez et al., 2022). New longitudinal studies, perhaps with future SHARE data, could address this question and extend this study allowing pre-post Covid-19 comparisons. Another aspect to improve would be to reach a consensus on which structural and functional variables should be used for the classification. This would make it possible to easily compare research and to accurately study whether the different classifications found are due to cultural differences and not to the different criteria employed.

Finally, knowing which social network groups exist and how they are distributed in each country makes it possible to improve the design of social service programs (Fiori et al., 2006). There is a relationship between network typologies and use of health services (Wenger, 1997), some studies have found that older adults in rich social networks were more likely to use complementary and alternative medicine (CAM) (Litwin & Shiovitz-Ezra, 2011) and groups with diverse and couple-centered networks were more predisposed to use traditional medicine than people in restricted networks (Park et al., 2018b). People with diverse and connected networks have more opportunities to share information and use health services. However, people with restricted networks and therefore limited social support, may lack the means or motivation to use health care despite having the highest health needs (Litwin, 1997). Further research on how to encourage individuals with restricted networks to increase their use of health services is needed. This type of research is worth conducting, given that using health services at the onset of problems helps to treat them appropriately and could avoid chronic or more severe problems.

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Table 1. Fit statistics, entropy, and statistical model comparisons

Profiles	*AIC*	*BIC*	*SSA-BIC*	*Entropy*	*p LMR*	*p BLR*
1	1975030.171	1975160.977	1975110.129	NA	NA	NA
2	1943717.239	1943921.623	1943842.173	0.977	<.001	<.001
3	1915145.506	1915423.468	1915315.417	0.977	<.001	<.001
4	1888280.683	1888632.223	1888495.570	0.955	<.001	<.001
5	1862585.030	1863010.148	1862844.894	0.967	<.001	<.001
6	1837044.945	1837543.641	1837349.784	0.972	<.001	<.001

Note: AIC= Akaike Information Criterion; BIC=Bayesian Information Criterion; SSA-Bic=Sample-Size-Adjusted BIC; LMR=Lo–Mendel–Rubin test; BLRT = Bootstrapped Log-likelihood Ratio Test; NA = Not applicable. *N*= 26248, included all the respondents with at least one person in their social network.

Table 2. Confidant network types by criterion variables

Criterion	Family N= 15742	Friends N= 4686	Spouse N= 3097	Diverse N= 2187	Others N= 536	No network N= 1024	Total N=27272
Spouse/Husband	20.55	11.62	99.14	11.97	3.36	-	27.31
Children	56.15	14.85	0.31	26.31	4.02	-	38.43
Other family	18.69	10.82	0.53	13.95	2.08	-	14.36
Friends	4.37	62.20	0.01	12.48	1.70	-	14.96
Others	0.21	0.50	0.00	35.29	88.83	-	4.95
5 km proximity	60.94	57.46	99.32	62.66	78.24	-	65.69
Daily contact	51.04	27.12	99.45	33.87	37.43	-	50.84
Very close	91.70	76.56	95.67	72.94	57.40	-	87.21
Network size	2.98 (1.4)	3.38 (1.71)	1.00 (.00)	3.75 (1.34)	2.31 (1.56)	0.00 (0.00)	2.87 (1.56)

Notes: *N*= 27272, network size range: 0–7

Table 4. Principal network typology effect, means and standard deviation by profiles

	Profile 1 Family	**Profile 2 Friends**	**Profile 3 Spouse**	**Profile 4 Diverse**	**Profile 5 Others**	**Profile 6 No network**	***F***	***η^2***	**Post hoc comparisons**
Health									
Chronic diseases	2.20 (1.66)	2.01 (1.57)	2.00 (0.03)	2.35 (1.73)	2.51 (1.74)	2.80 (2.06)	52.77	.010	1>2,3; 4>1,2,3; 5>1,2,3; 6>1,2,3,4,5
Perceived health	2.69 (0.98)	2.91 (1.00)	2.69 (1.00)	2.68 (1.02)	2.39 (1.02)	1.98 (1.01)	156.26	.028	1>2; 3>2; 4>2; 5>1,2,3,4; 6>1,2,3,4,5
Well-being									
Quality of life	37.29 (6.36)	38.75 (5.68)	37.04 (6.34)	37.58 (6.08)	35.71 (6.64)	33.94 (7.32)	81.74	.016	1<2; 3<2; 4<2; 5<1,2,3,4; 6<1,2,3,4,5
Life Satisfaction	7.86 (1.67)	7.91 (1.54)	7.92 (1.64)	7.82 (1.62)	7.19 (1.95)	6.86 (2.29)	52.51	.010	5<1,2,3,4; 6<1,2,3,4,5
Mental health									
Loneliness	3.97 (1.41)	3.89 (1.31)	3.80 (1.28)	4.06 (1.42)	4.53 (1.74)	4.91 (1.95)	76.77	.015	1>2,3; 2>3; 4>2,3; 5>1,2,3,4; 6>1,2,3,4,5
Depression	2.42 (2.27)	2.36 (2.08)	2.12 (2.18)	2.69 (2.25)	3.07 (2.54)	3.45 (2.77)	47.55	.009	1>3; 2>3; 4>1,2,3; 5>1,2,3,4; 6>1,2,3,4
Cognitive function									
Memory	4.25 (1.79)	4.82 (1.72)	4.18 (1.79)	4.29 (1.79)	3.76 (1.78)	3.40 (2.05)	120.94	.023	1<2; 3<2; 4<2; 5<1,2,3,4; 6<1,2,3,4,5
Fluency	19.40 (7.46)	21.43 (6.99)	19.08 (7.46)	19.91 (7.14)	17.44 (7.15)	15.86 (7.82)	100.35	.019	1<2,4; 3<2,4; 4<2; 5<1,2,3,4; 6<1,2,3,4,5

Table 5. Probability of network profile in each European region and the chi-square differences

Criterion		Family	Friends	Spouse	Diverse	Others	No network	Marginals
North	%	52.4%	24.7%	8.6%	10.4%	1.6%	2.3%	12.6%
	Adj. Res	**-7.0**	**12.9**	**-5.5**	**5.6**	-1.5	**-4.9**	
Western	%	54.1%	22.9%	8.2%	9.6%	2.1%	3.1%	36.0%
	Adj. Res	**-9.6**	**19.4**	**-12.3**	**7.5**	1.0	**-4.3**	
South	%	64.3%	11.0%	14.5%	3.5%	1.3%	5.5%	19.1%
	Adj. Res	**10.3**	**-12.8**	**7.9**	**-13.4**	**-4.0**	**7.6**	
Eastern	%	69.6%	10.9%	14.1%	7.9%	2.4%	4.0%	32.3%
	Adj. Res	**6.2**	**-18.3**	**9.9**	-0.3	**3.4**	1.5	
Marginals		58.0%	17.0%	11.4%	8.0%	2.0%	4.0%	100%

Note. In bold adjusted residuals that exceed +/- 3

Table 6. Means and standard deviations of the interaction between network typologies and regions of Europe

Characteristics	Family	Friends	Spouse	Diverse	Others	No network	*F*	η^2
Chronic diseases							3.15***	.002
North	1.81 (1.45)	1.81 (1.47)	1.77 (1.53)	1.99 (1.56)	2.11 (1.37)	2.23 (1.55)		
Weast	2.08 (1.65)	1.94 (1.59)	2.03 (1.73)	2.21 (1.68)	2.35 (1.68)	2.64 (2.18)		
South	2.27 (1.63)	2.14 (1.52)	1.93 (1.49)	2.77 (1.84)	3.31 (1.88)	2.93 (1.91)		
East	2.41 (1.73)	2.29 (1.62)	2.09 (1.60)	2.63 (1.79)	2.54 (1.78)	2.95 (2.14)		
Self-perceived health							1.37	.001
North	3.17 (1.09)	3.25 (1.09)	3.25 (1.11)	3.15 (1.14)	2.70 (1.06)	2.44 (1.11)		
Weast	2.85 (0.97)	2.97 (0.98)	2.84 (1.02)	2.78 (0.98)	2.55 (1.06)	2.15 (1.07)		
South	2.59 (0.93)	2.71 (0.92)	2.72 (0.96)	2.39 (0.97)	2.20 (1.03)	1.94 (1.02)		
East	2.43 (0.89)	2.60 (0.91)	2.44 (0.92)	2.38 (0.91)	2.20 (0.92)	1.76 (0.88)		
Quality of life							3.44***	.002

North	39.83(5.03)	40.27 (4.70)	40.47 (5.02)	39.82 (5.03)	39.49 (4.98)	37.30 (7.50)		
Weast	39.67 (5.34)	39.80 (5.25)	39.65 (5.54)	38.60 (5.81)	37.13 (6.34)	36.68 (7.15)		
South	33.67 (6.68)	35.30 (6.14)	33.76 (6.15)	32.51 (6.62)	31.33 (6.37)	31.00 (6.76)		
East	36.36 (6.12)	37.00 (5.84)	36.55 (6.11)	36.42 (5.78)	34.73 (6.49)	32.51 (6.66)		
Life Satisfaction							1.50	.001
North	8.60 (1.34)	8.51 (1.40)	8.69 (1.32)	8.44 (1.39)	8.16 (1.46)	7.94 (2.45)		
Weast	8.12 (1.42)	7.97 (1.38)	8.26 (1.42)	7.99 (1.42)	7.42 (1.85)	7.37 (1.87)		
South	7.53 (1.73)	7.61 (1.51)	7.66 (1.51)	7.26 (1.69)	6.57 (1.52)	6.60 (2.18)		
East	7.57 (1.82)	7.42 (1.79)	7.67 (1.81)	7.43 (1.82)	6.93 (2.14)	6.33 (2.46)		
Loneliness							4.49***	.003
North	3.60 (1.08)	3.63 (1.09)	3.40 (0.97)	3.74 (1.11)	4.15 (1.60)	4.33 (1.75)		
Weast	3.67 (1.12)	3.78 (1.21)	3.66 (1.17)	3.98 (1.38)	4.22 (1.59)	4.49 (1.81)		
South	4.49 (1.75)	4.33 (1.65)	4.12 (1.41)	4.92 (1.83)	5.39 (2.08)	5.34 (2.07)		
East	4.07 (1.42)	4.15 (1.39)	3.78 (1.29)	4.10 (1.39)	4.70 (1.70)	5.17 (1.94)		
Depression							4.12***	.002

North	1.85 (1.82)	2.00 (1.85)	1.47 (1.72)	2.09 (1.78)	2.96 (2.06)	2.28 (2.16)		
Weast	2.19 (1.98)	2.34 (2.04)	2.04 (2.01)	2.68 (2.25)	2.88 (2.31)	2.90 (2.33)		
South	2.72 (2.70)	2.42 (2.40)	2.21 (2.48)	3.61 (3.01)	3.53 (3.26)	4.01 (3.04)		
East	2.66 (2.32)	2.69 (2.10)	2.28 (2.17)	2.76 (2.14)	3.17 (2.63)	3.93 (2.93)		
Memory							2.05**	.001
North	4.63 (1.78)	5.10 (1.72)	4.38 (1.64)	4.69 (1.75)	3.85 (1.82)	3.98 (2.03)		
Weast	4.58 (1.79)	5.03 (1.71)	4.52 (1.88)	4.46 (1.80)	4.09 (1.72)	3.72 (2.16)		
South	3.50 (1.63)	3.88 (1.54)	3.68 (1.59)	3.29 (1.60)	3.14 (1.59)	3.05(1.84)		
East	4.26 (1.75)	4.66 (1.67)	4.23 (1.82)	4.11 (1.75)	3.61 (1.82)	3.19 (2.03)	1.43	.001
Fluency								
North	22.52 (7.61)	23.63 (6.98)	22.06 (6.72)	22.04 (7.93)	19.96 (7.91)	18.80 (8.29)		
Weast	20.61 (6.94)	21.75 (6.70)	19.94 (6.82)	20.20 (6.69)	18.23 (6.61)	17.01 (7.37)		
South	14.75 (6.21)	16.58 (5.72)	15.11 (6.56)	13.63 (5.38)	13.32 (6.46)	12.24 (6.56)		
East	20.04 (7.37)	21.65 (7.04)	20.23 (7.64)	20.07 (6.82)	17.27 (7.16)	16.19 (8.06)		

Note: *$p < .05$; **$p < .01$; ***$p < .001$. Chronic diseases range from 0 to 14, self-perceived health range from 1 to 5, quality of life range from 12 to 48, life satisfaction range from 0 to 10, loneliness range from 3 to 9, depression range from 0 to 12, memory range from 0 to 10 and fluency range from 0 to 100.