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The four year project (2015-19) is a collaboration between the three leading European Research Infrastructures in the social sciences – the European Social Survey (ESS ERIC), the Survey of Health Ageing and Retirement in Europe (SHARE ERIC) and the Consortium of European Social Science Data Archives (CESSDA AS) – and organisations representing the Generations and Gender Programme (GGP), European Values Study (EVS) and the WageIndicator Survey.

Work focuses on three key areas: Addressing key challenges for cross-national data collection, breaking down barriers between social science infrastructures and embracing the future of the social sciences.

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1. introduction

Work on social networks conducted as part of the SERISS project builds on initial work by SHARE and focuses on designing a ‘name generator’ for cross-national surveys. This tool allows respondents to name all close confidants and intensity of contact with these confidants. A key aim was to construct and translate computerized questionnaire items that can be used in longitudinal and cross-sectional settings for all social surveys. This work was documented in SERISS deliverable D8.21 (Litwin & Schwartz, 2016b). The current document reports on the subsequent work to generate a standardized classification of network types based on the data collected.

The background material presented in this Introduction comes from a chapter (Litwin, forthcoming) in a soon-to-be published book. As is reported in that chapter, the term "social network type," first coined by Clare Wenger (Wenger, 1991), constitutes a composite characterization of the nature and the extent of one's interpersonal environment (Fiori, Smith, & Antonucci, 2007). It permits analysis as to how social interconnectedness can interplay with well-being in late life. Network types have been shown to predict morale (Litwin, 2001), anxiety, loneliness and happiness (Litwin & Shiovitz-Ezra, 2011), depressive symptomatology (Fiori, Antonucci, & Cortina, 2006), physical health (Litwin, 1998), functional dependency (Doubova, Perez-Cuevas, Espinosa-Alarcon, & Flores-Hernandez, 2010) and mortality (Litwin & Shiovitz-Ezra, 2006).

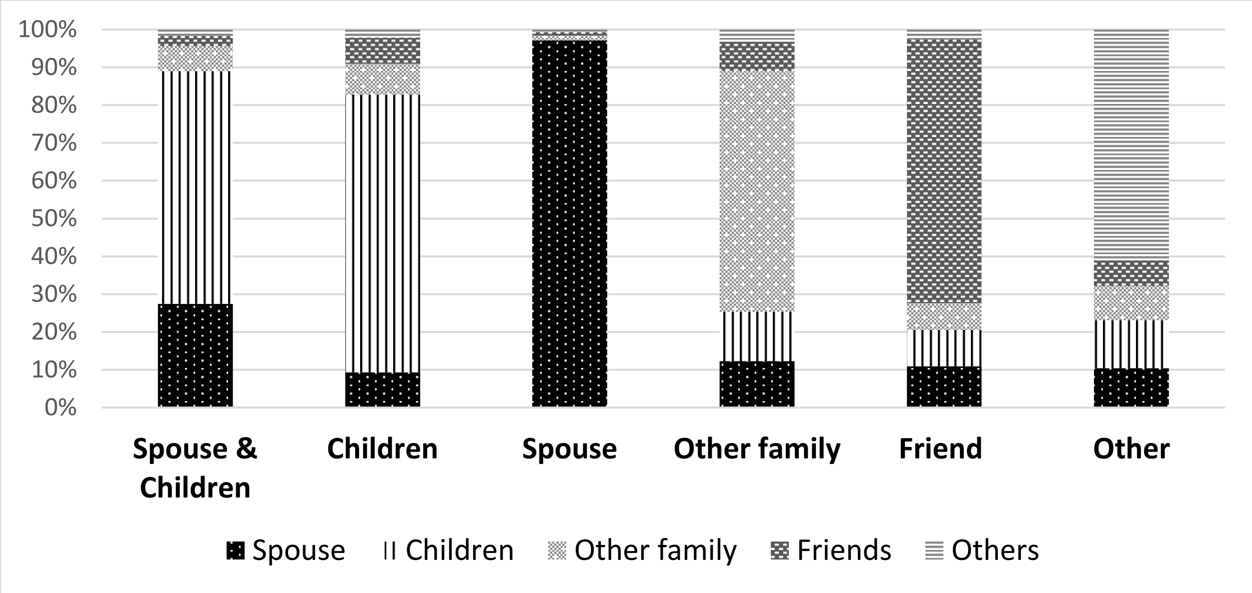
Previous work on social networks

An initial study derived network types from the SHARE social network (SN) data from the fourth wave of the survey (the first time the SN module was administered). K-means cluster analysis was applied to eight network variables among respondents aged 65 and older (Litwin & Stoeckel, 2014). Five of the variables characterized the compositional character of the network. They indicated the proportion of the network comprised of the following relationship groupings, respectively: 1) spouse or partner, 2) children, 3) other family (e.g. siblings, grandchildren, etc.), 4) friends and 5) others (e.g. neighbors, colleagues, formal helpers). The remaining three variables in the clustering procedure took interaction into account: proximity, contact frequency and emotional closeness.

The results of this procedure are shown in Figure 1 in a graph that illustrates mainly the compositional character of the network. As can be seen, six network types were derived. The “spouse and children” network averaged two to three members, had high proximity, contact and emotional closeness, and accounted for almost a quarter of the study sample. The “children” network had three confidants, on average, and high emotional closeness, but somewhat lower proximity and contact frequency. Almost a fifth of the sample fell in this grouping. The "spouse" network numbered about one member only (the spouse). It exhibited the highest proximity, contact, and emotional closeness, and accounted for a bit more than a sixth of the sample.

The "other family" network had an average of three members, with somewhat high emotional closeness, but only moderate proximity and somewhat lower frequency of contact. Less than a sixth of the sample belonged to this network type. The "friend" network had three members, of which more than two thirds were friends, with moderate proximity and emotional closeness but low contact frequency. A bit less than a seventh of the sample were in the friend network type. Finally, the "other," network also reported having about three confidants who, while in moderate proximity, were low in contact and emotional closeness. Six percent of the study sample fell into this network grouping.

Figure 1: Social network types among older Europeans (65+)



The network typology also took into account the respondents who had no network at all, that is, those who did not name anyone when asked: "who are the people with whom you discuss important matters." Six percent of the study sample fell into this grouping and were thus classified as having "no network." They may be considered socially isolated in that they do not share important thoughts and/or feeling with others. Thus, the network typology encompassed the entire SHARE sample of persons aged 65 and older (n=28,697), including those having no confidants at all.

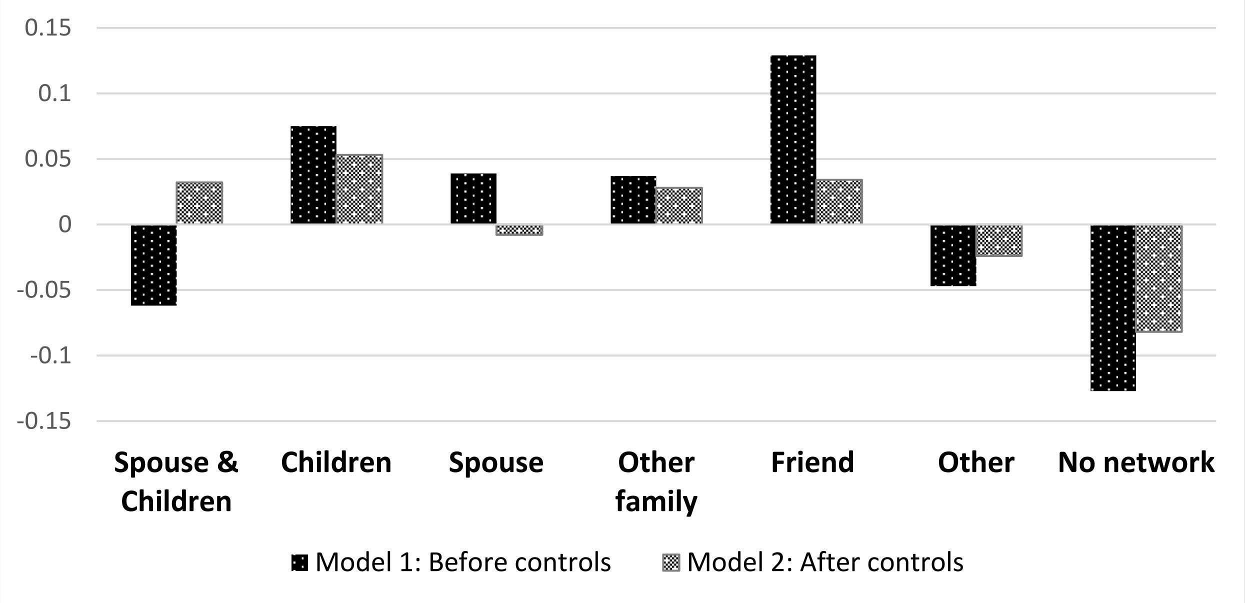
The study then looked at the association between social network type and positive well-being, as measured by the CASP Scale. It used the validated 12-item version of CASP that is employed in SHARE (Wiggins, Netuveli, Hyde, Higgs, & Blane, 2008). The scale reflects four quality of life domains: control, autonomy, self-realization and pleasure. Together, they offer an inclusive measure of the state of well-being.

Figure 2 shows a graph of the results of the statistical analysis, which regressed the respondents' well-being scores on the respective network types, controlling for country, age, gender, marital status, education, and mobility. The graph shows two statistical models. The first reflects the association between network type and well-being. The second presents the same after taking into account the respective effects of the control variables.

The dark bars (Model 1) show that two network types in the unadjusted analysis had the dominant effects on well-being. "Friend" networks were the most strongly positively related and having "no network" (the socially isolated) was the most negatively related. "Children," "spouse" and "other family" networks were positively associated with well-being (albeit more modestly) while "spouse and children" and "other" networks were negatively related. All the associations were statistically significant.

However, this picture changed somewhat after taking the control variables into account (Model 2). The "children" network emerged as the network type that was the most positively related with well-being. The "friend" and "spouse and children" networks were the second and third most positively related network types, respectively. The "other" family network type had a somewhat lower but still positive correlation with the well-being score. In contrast, the "spouse" network type became unrelated to the well-being measure, perhaps because of having adjusted for marital status in the second model. Respondents in the "other" network retained a modest negative correlation with the well-being outcome. Most importantly, those having no confidants (the "no network" grouping) had the strongest and the most negative association with the well-being indicator, all else considered.

Figure 2: Social network type correlates of well-being among older Europeans (65+) before and after controlling for country and background characteristics: Beta weights



Model 2 adjusted for country, age, gender, marital status, education, and mobility.

This analysis underscored that a composite measure of the interpersonal environment—network type—can effectively distinguish between older people having better and worse well-being. It showed, moreover, that those with greater social capital as reflected by the different network types had better well-being as well. In addition, the study confirmed that social isolation, or lack of a social network, is a strong correlate of poor well-being, beyond the effects of several other predictor variables.

This report

The work that has led to the production of the current deliverable is based upon a dual strategy. The first main aim of the work is to validate the network typology that was previously derived from the SHARE Wave 4 data using the SHARE Wave 6 data. The results of this effort are reported in the next section. A corresponding aim is to trace the network type changes across the two waves, to the extent that they occurred, and to identify the socio-economic and health correlates of such network type shifts.

The second main aim of the work is to derive a network change typology based upon on the SHARE sample of adults aged 65 and over. Toward this aim, K-means cluster analysis is applied to all respondents who participated in both of the waves in which the social network data were collected. The results of this procedure are discussed in Section 3. Section 4 provides general guidance on constructing network typologies. The changes in older adults' social network types are still poorly understood, and their delineation will shed light on the complex social processes that occur in old age, with significant implications for the availability of support and resources.

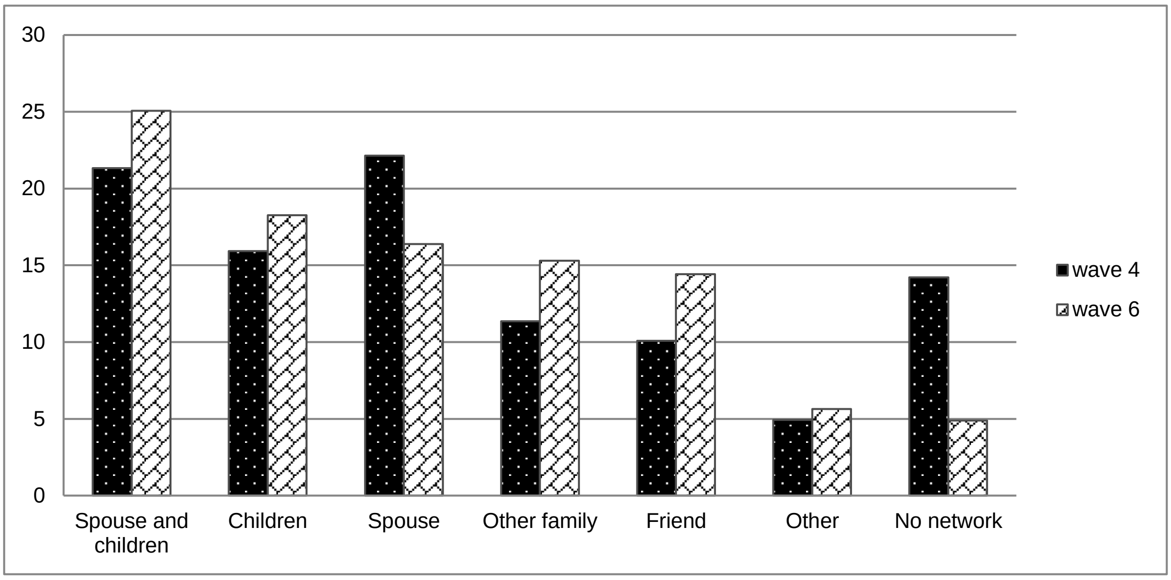
2. Wave 6 Network Typology

As discussed in the previous section, the data from Wave 4 showed a clear typology of networks types, based on compositional and interactional criteria. Using Wave 6 data, we applied the same methodology used in Wave 4, in order to validate the typology. For this purpose, we ran the K-means cluster analysis on a sample of Wave 6 respondents 65 and older in all participant countries excluding Croatia (which did not participate in Wave 4). We ran this procedure several times, which all resulted in the same pattern of six network types in addition to the "no network" type. We chose the solution that provided the closest similarity to the typology of wave 4.

All the seven types of social networks demonstrated almost identical prevalence rates as in Wave 4, with minor exceptions. The types "Other" and "Spouse" were reduced by one percent, while "Spouse and children" and "Friend" showed a one percent increase. In addition, the networks we found closely replicated the internal composition and interaction indicators found in Wave 4, again with minor exceptions. In Wave 6 the "Friends" network exhibited slightly less emotional closeness, and the "Other" network was composed of 46 percent other people from the network in comparison to 61 percent in wave 4. In general, analyses of wave 6 revealed considerable congruence with Wave 4.

To better understand network change, we examined transitions among the respective network types across the two waves. We related exclusively to the people who were interviewed in both waves in order to see how their networks changed after 4 years and what characterizes the changes. Figure 3 presents a graph illustrating the network typology for the respondents who participated in both waves. It can be seen that the relative distribution of some of the types tended to increase over the years – "Spouse and children", "Children", "Friends" and "Other family", whereas "Spouse" and "No network" decreased in their frequency. The "Other" network type stayed closer to its distribution in Wave 4.

Figure 3: Relative distributions of social network types in Waves 4 and 6 among participants in both waves



Beyond the general observation on the proportion of network types, we were also interested in the transition of individuals between these network types. We observed that more than 33 percent of the whole sample remained stable between the two time points. However, among those who did transition to a different type, some network types were more apt to change than others. Among individuals typified as “No network” and “Other”, less than 20 percent remained in these network types, whereas among those in the “Spouse and children” networks, 48 percent remained stable. We thus find that network types characterized by emotional closeness (as discussed in the previous section) are more stable than those which are less emotionally close.

Looking at transitions in the whole sample, we observed four prominent transition statuses:

(1) Stable close-family type. This grouping is characterized by stability or transitions between the three close-family network types (“Spouse and children”, “Children” and “Spouse”).

(2) Stable less-close type. This grouping is characterized by stability or transitions between the three less-close types (“Other family”, “Friends” and “Other”).

(3) Change from less-close to close-family networks. These are mostly individuals who were classified as “Other family”, “Friends” or “Other” networks in Wave 4, but transitioned to one of the three close-family networks.

(4) Change from close-family to less close networks. These are individuals who were classified as “Spouse and children”, “Children” or “Spouse” networks in Wave 4, but transitioned to one of the three less-close networks

In order to characterize these transition groups, we examined how they correlate with socio-economic and health variables. The correlations are reported in Table 1 (only significant correlations are shown). The transition type of “Stable less-close” showed significant differences from the others types. This transition type was characterized by gender (more women), better education, better self-rated health, and higher levels of well-being. It could be that these respondents who apparently enjoy relatively better life circumstances did not need to seek different social networks and remained mostly in contact with people outside the close family. On the other hand, those who remained in stable close-family networks tended to be male, less educated, and had poorer self-rated health and lower levels of well-being. It seems that these respondents tended to stick with their family network and were less open to other options. The other two transition types were similar to one another on these same variables.

Table 1: Socio-economic and Health by four types of Network Transition: Analysis of Variance

Characteristics	Network transition type: Stable close-family	Stable less-close	Less-close to close-family	Close-family to Less close	*F*
% Women	43.0	57.7	51.1	51.8	38.92***
% Secondary/high education	49.5	63.4	58.7	58.3	37.33***
Rated poor health	0.57	0.47	0.51	0.51	15.71***
CASP-12	36.4	37.9	37.1	37.1	20.91***

**** p<0.001*

Finally, we were especially interested in the respondents who were classified as "No network" in Wave 4 and then made a transition to a different network type in Wave 6. We termed the respondents making this particular transition the "No longer loners." We compared them to those that stayed with their no network status in Wave 6 as well, a group we named the "Loners". Some 52 percent of the loners in Wave 4 of SHARE became no-longer loners in Wave 6. Correspondingly, 48 percent remained loners.

We also examined the correlations between these particular network change types to the background and well-being variables. The significant results are shown in Table 2. In comparison to the respondents who remained in their no-network situation (the Loners), the "No longer loners" were older, less educated, less healthy and more disabled. It could be that their disadvantaged state pushed them to seek assistance from a social network (any social network). The data also showed, however, that the "No longer loners" group reported higher satisfaction from life. It is tempting to conclude that their greater life satisfaction was a result of the shift from "Loner" to "No longer loner" status, but this observation requires further corroboration.

Table 2: Socio-economic and health by network transition type of loners: Analysis of variance

Characteristics	Network transition type: "Loners"	"No longer loners"	*F*
Age	64.7	71.8	103.06***
% Secondary/high education	0.55	0.44	5.98*
Mobility limitations	1.71	2.56	13.29***
% 2+ chronic diseases	0.32	0.42	5.36*
Life Satisfaction	1.95	2.09	22.54***

**** p<0.001 *p<0.05*

3. Network Change Typology

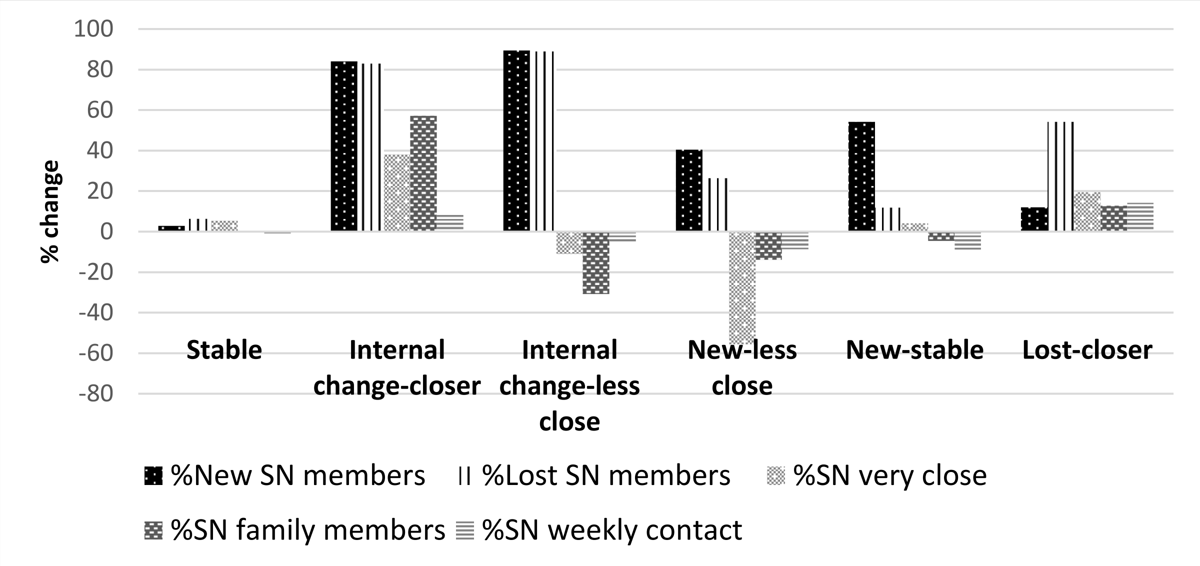
As described above, social network typologies have been used to describe older persons' complex patterns of social relationships. However, social networks are dynamic and the patterns of social changes can differ among adults, especially in old age. Currently, there is little understanding of the types of social network change that can occur in later life. The second aim of the current work therefore is to identify different social network change patterns among older adults. We explain the construction of these network types, specify their validation process and describe the dispersion of the types among the participants in SHARE Wave 6. Part of this work was presented as a poster in the 24th Nordic Congress of Gerontology, which was held in Oslo, Norway, in May 2018.

The types of social network change were derived from data from Waves 4 and 6 of SHARE. The analyses focused on adults aged 65+ who participated in both waves and had social network data in both measurement periods. K-means cluster analysis was applied to five variables indicating different aspects of network change: 1) the proportion of new members within the social network, 2) the proportion of members lost from the social network, 3) an indicator of change in the proportion of weekly contacted confidants, 4) an indicator of change in the proportion of family confidants and 5) an indicator of change in the proportion of emotionally close confidants.

The optimal cluster solution identified six distinct types of network change (Figure 4). The first type reflects a stable social network ("stable"), meaning no change over the two measurement periods. The next two types are characterized by extensive internal turnover. The internal changes in question were accompanied by either a) an increase in the emotional and familial qualities of the network ("internal change-closer") or b) by a decrease in these aspects ("internal change-less close"). Two additional network change types reflect the transitions among those older adults who reported having more newly added social network members, resulting in an overall increase in the network's size. This change was accompanied by either a) a decline in the emotional closeness of the network ("new-less close"), or b) by stability in the networks' qualities ("new-stable"). The sixth and last type of change consisted of having lost more social network members than were added, resulting in a smaller network, accompanied by an increase in the emotional closeness and contact frequency of the network ("lost-closer"). The six network change types are, thus:

1. Stable
2. Internal change-closer
3. Internal change-less close
4. New-less close
5. New-stable
6. Lost-closer

Figure 4: Social network change types and their characteristics



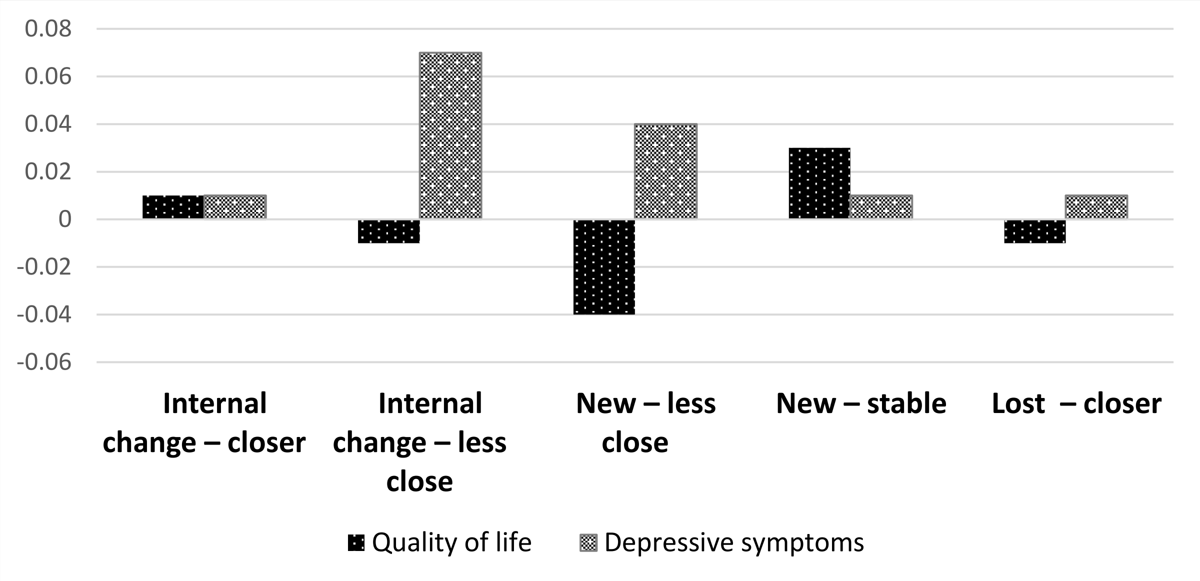
The socio-demographic characteristics of persons experiencing the respective patterns of social network changes are shown in Table 3. Those whose networks underwent internal turnover and became less emotionally close were older, more likely to be women and less educated. On the other hand, men tended to experience more stable networks over time. These results might indicate that persons who are relatively disadvantaged (older and less educated) also experience instability in their social relationships and a deterioration of the quality of their close ties, possible decreasing even further their access to resources.

Table 3: Social network change types and socio-demographics characteristics

	Network change type					
Characteristic	**Stable**	**Internal change-closer**	**Internal change-less close**	**New-less close**	**New-stable**	**Lost-closer**
Age	72.7	73.1	73.4	72.8	72.7	72.9
Gender (women)	53%	58%	64%	59%	57%	59%
Education (secondary+)	52%	50%	47%	55%	52%	53%

Two multiple regression models (OLS) predicted two well-being outcome measures (quality of life and depressive symptoms) in relation to the six network change types (Figure 5). The results show that when the network grew but became less emotionally close ("new-less close"), the older adults in question reported lower quality of life and more depressive symptoms. A higher depression score was also associated with the change type experiencing internal turnover accompanied by decreased network quality ("internal change-less close"). On the other hand, quality of life was seen to improve among older adults' whose networks grew while the quality of their networks remained stable ("new-stable").

Figure 5: Social network change type correlates of depressive symptoms and well-being among older Europeans (65+): Beta weights



Reference category: stable social network

The models are adjusted for the social networks at baseline (size, proportion of kin, proportion of emotionally close confidants and proportion of confidants contacted weekly), age, gender, education, mobility limitations, memory score and depressive symptoms \ quality of life at baseline.

These analyses emphasize that there are diverse ways in which social relationships can change in later life. Their identification captures the subtle nuances behind these dynamics. Moreover, the emergence of several different change patterns challenges the assumption of a homogenous trend of social changes in old age. The analysis also shows that some change types differ in their consequences for mental health. Specifically, changes to network structure accompanied by declines to the emotional and familial aspects of the network were related to poorer mental health. This underscores the importance of maintaining an emotionally meaningful close network, even as members are added or removed from it. Thus when older adults add ties to their close milieu, they should preferably be emotionally close relationships.

4. A Guide to Creating Social Network Typologies

Network types may be derived through several analytic procedures for data reduction. One such recommended procedure is K-means cluster analysis in which designated criterion variables are employed to identify relatively homogeneous groupings in a population of interest. The process uses an algorithm that can handle a large number of cases, a characteristic particularly suitable for large scale surveys such as SHARE. In the K-means cluster procedure, initial cluster centers are assigned for each of a number of selected criterion variables and are then iteratively updated until optimal groupings are achieved based upon Euclidean distance (See Milligan & Cooper, 1987 and Rapkin & Luke, 1993 for additional recommendations for running K-means cluster analyses).

It should be noted that this statistical procedure is essentially an exploratory one, insofar as the researcher selects in advance the number of clusters to be derived in each trial. In analysis of the network types based on SHARE data, cluster combinations of four, five, or six groupings are frequently tested, as described above. Three guiding principles must be taken into account in any network clustering procedure. First, the criterion variables employed must reflect the specific aims of the researcher. That is, different analyses may employ different sets of criterion variables. Second, the criterion variables employed in the clustering procedure should be measured on similar scales, or should be otherwise standardized before the clustering process takes place. The third guiding principle is that the ultimate preferred solution is the choice of the analyst (backed up by prior evidence, if it exists). The researcher must identify the optimal cluster solution, that is, the number of clusters that best reflects the field of inquiry, to be employed in the analysis. The preferred solution is based upon the distinctiveness of one cluster from another, the parsimony of the overall cluster set, the theoretical relevance of the derived groupings and the degree to which the solution is grounded in established knowledge.

Researchers constructing a typology of social networks at one time point can use the eight criterion variables noted earlier (Litwin & Stoeckel, 2014). The first five variables, which characterized the relationship compositional character of the confidant network grouping, reflect the proportion of the named network composed of the following relationship groupings: (a) spouse or partner, (b) children, (c) other family, (d) friends, and (e) others. The other category is composed of neighbors, (ex-)colleagues, or formal helpers. The remaining three criterion variables take into account the relational dynamics. Proximity is measured as the proportion of cited confidants who resided within 5 km of the respondent's residence. Contact is calculated as the proportion of named confidants with whom the respondent maintained daily contact. Emotional closeness is indicated as the proportion of cited persons with whom the respondent felt very or extremely close. Respondents without a confidant network are defined as those who did not name anyone and this "no network" category is added to the collection of derived network clusters. The optimal cluster solution identifies six distinct confidant network types and one additional grouping having no such ties.

In constructing typologies of network change over time, it is recommended that researchers use the five criterion variables noted above: 1) proportion of new members of the social network, 2) proportion of lost members of the social network, 3) change in the proportion of weekly contacted confidants, 4) change in the proportion of family confidants and 5) change in the proportion of emotionally close confidants. The optimal cluster solution for such a network change typology was found to be six clusters.

A more recently applied method for network typology derivation entails the use of latent-class analysis (LCA) (see for example: Ellwardt, Aartsen, & van Tilburg, 2017; Jacobs, van Groenou, Aartsen, & Deeg, 2018; Kim, Park, & Antonucci, 2016; Nguyen, 2017; Park et al., 2018; Windsor, Rioseco, Fiori, Curtis, & Booth, 2016). LCA is a model-based clustering analysis technique in which a statistical model (a mixture of probability distributions) is postulated for the population based on a set of sample data. Common applications of LCA are in health and clinical research and recently also in social and psychological studies. This technique might offer several advantages over traditional clustering approaches such as K-means; It assigns a probability to the cluster membership for each data point instead of relying on the distances to biased cluster means, it provides various diagnostic information, and it allows for the inclusion of demographics and other exogenous variables either as active or inactive factors (Magidson & Vermunt, 2004).

Few studies using SHARE data have employed the LCA procedure thus far. However, a recently published paper applied latent class analysis to the SHARE social networks data (Djundeva, Dykstra, & Fokkema, 2018). That study focused on older adults living alone, as they might be more at risk of lacking necessary supports. It examined how their social networks contribute to their subjective well-being and why some of them fare better. The study found four social network types among older adults living alone: “restricted”, “child-based”, “friend oriented” and “diverse”. The likelihood of having “restricted” and “child-based” networks was greater in Eastern and Southern European countries, whereas the likelihood of having “friend oriented” networks was greater in Western and Northern European countries. Across countries, those with “restricted” networks tended to have the poorest well-being. Those with “diverse” networks had even better well-being than older people who were co-residing with others. This study demonstrates that the SHARE social network data are already in use by analysts, with specific use being made of network typology construction. It also showed the importance of drawing distinctions within the group of older adults living alone and emphasized that most of them (two thirds) are not vulnerable or at risk. They tend to fare as well or even better than peers who co-reside with others.

5. Summary

The purpose of Task 8.8 was to build on the initial work by SHARE and design a ‘name generator’ for cross-national surveys which lets respondent name all close confidants and intensity of contact. It aimed to construct and translate computerized questionnaire items that can be used in longitudinal and cross-sectional settings for all social surveys and to generate standardized classifications of network types. The current deliverable focused on the construction of social network types and their changes across time, building upon developments described in previous deliverables. The derivation of the network typologies was based on the name generator module in SHARE, in which respondents identify the people who are important to them and then add information on each person named (D8.20, Litwin and Schwartz 2016a). The name generator tool was translated to the different national languages of the countries participating in SHARE, allowing for a comprehensive mapping of older Europeans‘ social networks (D.821, Litwin and Schwartz, 2016b). Given the significance of the social network construct to older adults‘ health and well-being, this work provides researchers with a rich and extensive data source on the social networks in Europe, promoting research on the social aspects of aging.

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