Social Networks 78 (2024) 164–172

Contents lists available at ScienceDirect

Social Networks

journal homepage: www.elsevier.com/locate/socnet

Older adults' mental health during the COVID-19 pandemic: The association with social networks

Zaira Torres *, Amparo Oliver, Irene Fernández

Department of Methodology for the Behavioral Sciences, University of Valencia, Spain

ARTICLE INFO

Keywords:
Social network
COVID-19
Mental health
Older people

ABSTRACT

This study examined the impact of different social networks on the mental health outcomes of older adults during the COVID-19 pandemic. Participants were 25,534 older adults from the Survey of Health, Ageing and Retirement in Europe (SHARE). The study identified five social network profiles (family, friends, spouse, diverse, others) and a "no network" group. Findings showed that, compared to the no network profile, those with spouse and family profiles are more protected against depression and loneliness during the COVID-19. In turn, individuals within friends and diverse profiles had a similar likelihood of feeling depressed, anxious, and lonely. Friends and diverse profiles had higher likelihood of suffering more anxious or lonelier than before the COVID-19 compared to the no network profile. The study further discusses possible explanations about why these profiles, which typically served as mental health protectors, were significantly affected by the unique circumstances of the COVID-19 pandemic.

Introduction

The COVID-19 pandemic has had a significant impact on individuals and communities worldwide. Beginning in March 2020, many countries implemented measures to reduce the spread of the disease, including stay-at-home orders and physical distancing mandates, such as minimizing physical contact with others and avoiding public social spaces and activities (Plümper and Neumayer, 2022). Older adults were identified as the population group with the highest risk of severe disease progression and death in case of infection with COVID-19 (Posch et al., 2020). Therefore, contact with older adults was explicitly discouraged. Consequently, several studies arose regarding the potential impact of social distancing measures on older adults' depression, anxiety, and feelings of loneliness (Berniell et al., 2021a, 2021b; Bundy et al., 2021; Krendl and Perry, 2021).

Evidence shows that social contact and social networks play a key role in maintaining mental health in old age (Fiori et al., 2006; Wenger, 1997). Social networks provide support, companionship, and coping strategies, which are important in times of stress and uncertainty, which were particularly salient during the COVID-19 pandemic (Coleman et al., 2022). For that reason, several studies have focused on studying which aspects of social networks may have played a protective or risk role in older adults' mental health outcomes during the pandemic (Arpino et al., 2022; Atzendorf and Gruber, 2021; Coleman et al., 2022; Kovacs et al., 2021; Skałacka and Pajestka, 2021; Van Tilburg et al., 2021).

Some studies have examined relationship dynamics of people within social networks. For example, the study of Coleman et al. (2022), in a sample of people aged 57 years and older from the United States, found an association between having greater closeness with other individuals within the social network and feeling less lonely and depressed during the first's months of COVID-19. In addition, Kovacs et al. (2021) found that older people with fewer than five "very close" relationships reported an increase in loneliness after the onset of the pandemic, while another study found that individuals having at least once a week contact with others within their social network reported feeling less depressed since the outbreak of the pandemic (Atzendorf and Gruber, 2021). In its part, Skałacka and Pajestka (2021) found that frequency of face-to-face contact of parents with their children was associated to better mental health results.

Other studies examined the nature of the relationship between the individual and people from their social network. A study carried out in a sample of older people from the Netherlands found that contact with children was associated with less loneliness at the beginning of the pandemic (Van Tilburg et al., 2021). Another study focused on older people who did not have traditional family ties, such as a partner or

* Correspondence to: University of Valencia, Department of Methodology for the Behavioral Sciences, Av. de Blasco Ibáñez, 21, Valencia, Valencia 46010, Spain.
E-mail address: zaira.torres@uv.es (Z. Torres).

https://doi.org/10.1016/j.socnet.2024.02.003

Available online 28 February 2024

children, and showed that these individuals were at higher risk of loneliness during the COVID-19 (Arpino et al., 2022). Also, having a more diverse composition of the social network has been related to a higher likelihood of feeling anxious during the COVID-19 (Coleman et al., 2022).

All, these results have shed light onto the ways some social network variables may have influenced older adults' mental health during the COVID-19 pandemic. However, to our knowledge, there is little research examining the study of social networks typologies and their association to mental health outcomes during the COVID-19 pandemic.

Establishing typologies of social networks has been shown to be a useful approach to study the characteristics of social networks and to capture their multidimensional aspects. Wenger (1991) was one of the first authors that started the classification of older adults according to their support network's typology. In this study, Wenger (1991) found five social network typologies representing older adults' relationship dynamics in the UK, considering several aspects of the social network, such as proximity, interaction, and proportion of relatives, friends, and neighbors within the network. More recent studies in the field have employed mixture modeling techniques such as Latent Class Analysis (LCA) or Latent Profile Analysis (LPA) to depict social network classes or profiles among older adults (Cohn-Schwartz et al., 2021; Harasemiw et al., 2019; Lestari et al., 2022). In general, four solid categories in the typologies have been reported in most studies (Cheng et al., 2009; Choi et al., 2022; Fiori et al., 2006; Litwin, 2001; Litwin and Stoeckel, 2014; Ye and Zhang., 2019): family, friends, diverse (which include family together with neighbors and friends) and restricted or no network (characterized for having minimal or no ties). However, study comparison is hindered by the discrepancies in the definition of social networks and the variables employed to measure them.

Some studies followed the Convoy Theory of Antonucci et al. (2014) and define social network as the amount and quality of relationships an individual has and from which they can receive support (Fiori et al., 2006; Harasemiw et al., 2019; Litwin and Shiovitz-Ezra, 2011; Park et al., 2015). To define social network groups, they include objective structural variables (as the number of relationship), dynamic variables (as frequency of contact) and variables that are related to community engagement (as social participation). Also, a study by Medvene et al. (2016) employed Antonucci's (1986) hierarchical mapping technique and included variables that were related to the inner, middle, and outer circle (people you can't imagine life without, people important for you and people close enough to be in your social network).

In addition, other studies are based on the so-called confidant approach. This approach is particularly relevant for deriving social network typologies as it focuses on the most meaningful people for the participant rather than assuming that all relationships in their life are important (Litwin, 1996). For example, in the study by Fiori et al. (2008) respondents were asked about the structural (network size, proximity) and functional (perceived instrumental and emotional support) characteristics of the 10 most important people in their network. Similarly, in the study by Litwin and Stoeckel (2014) participants were asked to list a maximum of seven people with whom they talked about important issues, and included variables related to the type of relationship with the person (family, friends.), proximity, contact and emotional closeness.

Regarding the relationship between social network typologies and mental health, most of these studies focused on the relation with depression (Cheng et al., 2009; Fiori et al., 2006; Harasemiw, 2019). These studies agree that people with greater depressive symptomatology are those who belong to the restricted network. Also, studies tend to find that older people with diverse networks followed by those with family or friend networks have lower levels of depression (Cheng et al., 2009; Fiori et al., 2006; Harasemiw, 2019; Wenger, 1997). However, some studies (Fiori et al., 2008; Lau et al., 2019) did not find statistically significant differences on depression among different social network groups.

Regarding older adults' mental health, literature also points to loneliness and anxiety as relevant correlates of social network profiles. For example, Medvene et al. (2016) found that the family group had the least feelings of loneliness in a sample of older people from the United States. In this line, Torres et al. (2023) found that individuals who belonged to the spouse network and to the friends network displayed the lowest levels of loneliness in a sample of European older adults. Finally, Litwin and Shiovitz-Ezra (2011) reported that older US adults that identified as having a diverse network were less anxious and less lonely than those who had a restricted network. Also, people with a family network or a friends network were less anxious than those with a restricted network (Litwin and Shiovitz-Ezra, 2011).

While previous literature suggests that support networks, such as those based on family, spouse, and friends, can be protective for older adults' mental health, the COVID-19 pandemic may have shifted this dynamic. For instance, larger support networks are generally associated with better health and well-being (Fiori et al., 2006; Litwin and Stoeckel, 2014), but during COVID-19, they could have become an additional source of stress, as they implied worrying about a larger number of people or being exposed to more sources of contagion (Coleman et al., 2022; Zhou and Guo, 2021). Furthermore, having children in one's social network is typically associated with perceiving more support and better health in old age (Harasemiw et al., 2019; Litwin and Stoeckel, 2014). However, during the COVID-19 lockdown and early stages of the pandemic, children living outside the home may have avoided visiting their parents for fear of infecting them.

In addition, research has shown several socio-demographic variables to be related to both mental health outcomes and the likelihood of belonging to specific social network profiles. For example, being a woman, lower socioeconomic status and physical limitations are associated to a higher risk of experiencing loneliness, depression, or anxiety during the pandemic (Mendez-Lopez et al., 2022; Scheel-Hincke et al., 2021; Steptoe and Di Gessa, 2021), these variables have also shown different prevalences in different social networks typologies (Litwin and Stoeckel, 2014).

Other studies have found that older age and living alone were associated with greater mental health problems during COVID-19 (Berniell et al., 2021a, 2021b; Maxfield and Pituch, 2020; Shevlin et al., 2020), while some other studies (Litwin and Stoeckel, 2014; Torres et al., 2023) showed these variables to be related to the no network and the others social network profiles. In addition, studies reported differences in older adults' mental health during COVID-19 across different countries (Lüdecke and von dem Knesebeck., 2022; Mendez-Lopez et al., 2022) and the study by Torres et al. (2023) showed that the prevalence of each social network profile differed across geographic regions in Europe.

Finally, individuals who witness others becoming ill or hospitalized, or even dying due to COVID-19 tend to experience greater worry, and mental health problems. In this line, research by Van Tilburg et al. (2021) shows that being personally affected by illnesses or deaths due to COVID-19 was associated with worse mental health. On the other hand, there is scarce literature examining social network profiles after the outbreak of the pandemic. To our knowledge, only the study by Li et al. (2023) examined mental health during COVID-19 employing social networks typologies, and these authors did not control for pandemic-specific variables such as those mentioned above.

Be that as it may, the study by Li et al. (2021) defined social network profiles based on the degree of support and assistance that individuals received from different sources (family, friends, community, institutions, and society), using a sample of Chinese adults. The authors found five network classes: 1) low social support, 2) predominantly proximal support, 3) predominantly remote support, 4) moderate social support, and 5) high social support. Across all age groups, family support was the most important for maintaining mental health and the class with high social support was more likely to experience better mental health. This classification showed that only a moderate to high level of perceived social support can protect older adults' mental health.

However, the study by Li et al. (2021) presents three main limitations: it does not distinguish between the type of support coming from children or partner and from other family members, it does not include aspects such as frequency of contact or closeness, and it uses a global measure of mental health.

Additional research distinguishing among different sources of support, using more specific measures of mental health, including measures of relationship dynamics and samples from other geographic regions would help enhance the understanding the impact of social networks typologies on the mental health of older adults during the pandemic. For that reason, this study aims to examine the different types of social support networks of older adults across Europe and Israel during the COVID-19 pandemic and their impact on depression, anxiety, and loneliness.

Method

Data and participants

The sample employed in this study comes from the Survey of Health, Ageing and Retirement in Europe (SHARE). SHARE is a multidisciplinary and international project that collects data on health, socioeconomic status, and social and family networks of people aged 50 or older across 27 European countries and Israel. In the SHARE sampling protocol, each country initially develops a sample design including the sampling frame to be used and specifying the sampling procedure. This preliminary design undergoes review and approval by the international coordinators at the SHARE headquarters. Then, the sample is drawn within each country and processed to generate a gross sample file. The gross sample is reviewed and approved by the international coordinators, who upload the data to a software in which data is later combined with the corresponding addresses. Further details about sampling can be consulted at Bethmann et al. (2019).

SHARE is a longitudinal panel study that started in 2004 and currently has eight regular waves of data or time-points, which are collected bi-annually, and two surveys designed to assess the impact of the COVID-19 pandemic whose data was collected in 2020 and 2021. The present study combined data from the 8th wave of SHARE (Börsch-Supan, 2022a), collected between October 2019 and March 2020, and the SHARE Corona Survey 1 (Börsch-Supan, 2022b), collected between June and August 2020. In wave 8, data was collected using Computer-Assisted Personal Interviews (CAPI). The interviewers conducted face-to-face interviews using a laptop computer on which the CAPI instrument was installed. For the SHARE Corona Survey 1, personal interviewing was not possible due to the outbreak of the pandemic. After careful considerations of the feasibility of different alternatives for SHARE's target population, it was decided that SHARE would resume interviewing with a Computer-Assisted Telephone Interview (CATI). (Bergmann and Börsch-Supan, 2021; Scherpenzeel et al., 2020). SHARE follows the ex-ante harmonization approach for the design of the questionnaire. It is developed starting from the English version, translated in 39 country-specific languages, and adapted to the national institutional framework. Data gathering was approved by the Ethics Council of the Max Planck Society, and all participants provided informed consent.

Waves 8 and Corona Survey 1 included a total of 36,838 participants that were interviewed in both waves. After excluding participants with missing data on all variables to conduct social network profiles, our final sample comprised 25,534 participants that were aged 65 or older at the beginning of the study period, the sociodemographic characteristics of the participants are included in Table 1.

Table 1
Sociodemographic characteristics of the participants.

	n (%) or Mean ± Standard Deviation
Age	74.63 ± 6.95
Women	14,593 (57.2%)
Austria	1073 (4.2%)
Germany	1668 (6.5%)
Sweden	978 (3.8%)
Netherlands	414 (1.6%)
Spain	918 (3.6%)
Italy	1362 (5.3%)
France	1288 (5.0%)
Denmark	984 (3.9%)
Greece	1873 (7.3%)
Switzerland	1282 (5.0%)
Belgium	1174 (4.6%)
Israel	644 (2.5%)
Czech Republic	1684 (6.6%)
Poland	1044 (4.1%)
Luxembourg	451 (1.8%)
Hungary	382 (1.5%)
Slovenia	1606 (6.3%)
Estonia	2063 (8.1%)
Croatia	692 (2.7%)
Lithuania	657 (2.6%)
Bulgaria	445 (1.7%)
Cyprus	318 (1.2%)
Finland	658 (2.6%)
Latvia	425 (1.7%)
Malta	441 (1.7%)
Romania	650 (2.5%)
Slovakia	360 (1.4%)
N	25,534

Instruments

Social network

Since there is no agreement in the literature about which criterion variables to employ in order to estimate the social network typologies, and the interest of this research lies in exploring changes in the COVID-19 context based on the results of pre-pandemic research, we will generate the social network typologies with the same eight variables used in two studies with SHARE data (Litwin and Stoeckel, 2014; Torres et al., 2023). The eight criteria or indicators for the latent profile analyses were taken from the generated social network module in SHARE. In the generated social network module, the participants were asked to list up to seven people with whom they regularly talked about important things. In addition, the participants were asked about some aspects of their relationship with the people they listed.

The first five variables inform about the percentage of people that the participant has in each category: (1) spouse (spouse or husband), (2) children (children or stepchildren), (3) other relatives (mother, father, brother, sister, grandchild, aunt, uncle, niece, nephew, and family in law), (4) friends, or (5) others (neighbors, former colleagues, and formal helpers). For each participant, we summed the total number of people who are in each category and divided by the total number of listed people. Finally, we multiplied this result by 100 to express the percentage of people of each type that makes up the social network. For example, if a person had a total of six people in the list, three of them belonged to the category of friends and three others to the category of children, the scores included in the analysis would show 50% friends and 50% children.

The remaining three variables reflect the "quality" or "dynamics" of the relationship between the participant and people of their network. The specific questions were the number of people that lived within a 1 km proximity of the respondent's home, with whom the individual had daily contact, and with whom the individual felt highly emotional close. Again, these variables were generated in the social network module. We divided these variables by the total network and multiplied by 100 to express the percentages of individuals in the social network who lived near the individual, had daily contact and were emotionally close.

Mental health variables

Depression, loneliness, and anxiety were assessed using different measures. For depression, participants were asked whether they had felt sad or depressed in the last month (Depressed, 0= no, 1=yes) from the Euro-D Depression scale (Prince et al., 1999). For those who answered "yes," a follow-up question assessed whether they felt more depressed during the pandemic (More depressed, 1= people who feel more depressed, 0= the rest of people who said that they don't feel depressed in the last month or that felt the same or less depressed during COVID-19).

Similarly, anxiety was measured using the item "In the last month, have you felt anxious or nervous?" (Anxious, 0=no, 1=yes). For those who answered "yes," a follow-up question assessed whether they felt more anxious during the pandemic (More anxious, 1= people who feel more anxious, 0 = the rest of people who said that don't feel anxious in the last month or that felt the same or less anxious during COVID-19).

Finally, feelings of loneliness were assessed by asking participants "How much of the time do you feel lonely?" (1=often, 2=some of the time, 3=hardly ever or never). Due to the low proportion of respondents who selected "Often" (less than 8%), we combined this category with "Some of the time" to create a binary measure (Lonely, 1=felt lonely often/some of the time, 0=felt lonely hardly ever or never). Those who felt lonely often or some of the times were further asked if they felt lonelier during the pandemic (Lonelier, 1= people who feel lonelier and 0= the rest of the people who said that don't feel lonely in the last month or that felt the same or less lonely during COVID-19).

Control variables

We controlled for several socio-demographic variables, including gender (0= men, 1 = women), age, ability of the participant to make ends meet (Ends meet) on a scale of 1–4 (higher scores indicating higher financial capacity), and mobility limitations with the global activity limitations (GALI) (1=limited or severely limited due to health problems, 0= no limited). Educational level was also controlled for using the International Standard Classification of Education 1997 (ISCED-97). The ISCED-97 is measured on a scale ranging from 0 to 6, where 6 indicates higher educational attainment (0=no education, 1= primary education, 2= lower secondary education, 3 and 4= higher secondary education, 5 and 6= tertiary education). To keep the maximum of information and variability we considered education as a continuous variable in the analysis. Additionally, we measured whether the respondent lived alone (Lives alone), and whether the person moved from its usual residence between June and August 2020 (House moved).

Additionally, we controlled for pandemic-specific variables which were whether the participant or anyone close to the participant: had COVID symptoms "Since the outbreak of Corona, did you or anyone close to you experience symptoms that you would attribute to the Covid illness?"; had COVID-19 "Have you or anyone close to you been tested for the Corona virus and the result was positive, meaning that the person had the COVID disease?"; was hospitalized due to COVID-19 "Have you or anyone close to you been hospitalized due to an infection from the Corona virus?"; or died due to COVID-19 "Has anyone close to you died due to an infection from the Corona virus?". In all cases, answers were recorded in a dichotomous scale (1= yes, 0= no).

Statistical analysis

To determine social support typologies, we employed Latent Profile Analysis (LPA) using Mplus 8.7 (Muthén, Muthén, 1998–2017). LPA is a statistical technique used to classify subgroups of observations that exhibit similar response patterns in relation to specific variables of interest. The main objective of LPA is to identify and define latent profiles or groups that share consistent and interpretable patterns of responses on the measures of interest. This method helps to maximize heterogeneity among these groups while ensuring homogeneity within each group.

Similar to cluster analysis, LPA is used to uncover hidden groups in the data by estimating the probability that individuals belong to different groups based on the distribution of their responses. However, we LPA was chosen as the preferred technique because it allows the use of test statistics and model fit indices to identify the best fitting number of profiles, which avoids biased results caused by different variances of the clustering variables (Magidson and Vermunt, 2002; Steinley, 2003). In addition, there is an increasing number of research in the field using mixture modeling techniques, such as LPA, to characterize social network types (Harasemiw et al., 2019; Lestari et al., 2022; Park et al., 2015).

First, a series of LPA models with increasing number of latent profiles are fitted. To determine the number of groups that best represent the different subpopulations within the data, the *k*-profile model is compared against the (*k*-1)-profile model (Marsh et al., 2009). In this study, up to six LPA models were fitted using eight social network variables.

Model comparison was done using several indices recommended in the literature (Ferguson et al., 2020; Nylund et al., 2007): Akaike's Information Criterion (AIC), Bayesian Information Criterion (BIC), sample size adjusted BIC (SSA-BIC), Lo, Mendell, and Rubin test (LMR), boot-strapped likelihood ratio test (BLR), and entropy. For AIC, BIC and SSA-BIC, lower values indicate better relative fit, although there is not a rule of thumb to consider the change meaningful (Masyn, 2013). For LMR (Lo et al., 2001) and BLR (McLachlan and Peel, 2000) statistically significant differences indicate better fit of the *k*-profile model against the (*k*-1)-profile model. Finally, entropy is a measure of classification and entropy values of at least 0.80 are considered as indicating good classification (Tein et al., 2013). In addition to model fit, we considered the interpretability of the profiles, as these ought to be interpretable (Lukočienė et al., 2010) and represent meaningful groupings of individuals (Ferguson et al., 2020).

After the establishment of social network profiles, we computed descriptive statistics of the eight social network variables used to characterize the profiles as to provide a general picture of social network profiles. In addition, descriptive statistics of sociodemographic, pandemic-specific, and the mental health variables were also computed for each profile. Next, six variables related to depression, loneliness, and anxiety feelings are regressed on social network types with a series of multilevel binary logistic regressions, setting country at the between-level variable and latent profiles at the within-level variable. Models were fully adjusted for covariates (age, gender, mobility limitations, ability to make ends meet, level of education, COVID-19 variables). To determine the strength of the relationship, odds ratios (OR) for each variable in the model are provided, with odds ratios lower than 1 indicating a lower likelihood of feeling depressed, anxious, or lonely compared to the reference category and odds ratio significantly higher than 1 indicating a higher likelihood of feeling depressed, anxious, or lonely compared to the reference category (Fernandes et al., 2020). To compare the magnitude of the odds ratios in the analysis of results, those less than 1 are transformed into (1/OR). All these analyses were conducted with SPSS 28 and Mplus.

Results

Latent profiles of social networks and their characteristics

After testing up to six latent profiles, the five-profile model was considered as the best solution and retained for further analysis. Results of model comparison fit statistics can be consulted in the Supplemental Material. The five profiles identified were labeled as family, spouse, friends, diverse and others. In case a respondent had reported a social network of size 0, they were allocated in an additional no network profile. We decided to label the groups in line with those reported by Litwin and Stoeckel (2014), since the resulting profiles resemble those reported by these authors. Mean scores on the eight criterion variables and average network size for each profile are available in Table 2. These mean scores represent the average percentage of people from each

Table 2
Summary statistics of criterion variables and average network size across social network profiles.

	Family n= 14,681		Friends n= 4128		Spouse n= 3556		Diverse n= 1732		Others n= 447	
Criterion	Mean %	SD	Mean %	SD	Mean %	SD	Mean %	SD	Mean %	SD
Spouse	30.54	15.51	19.17	17.57	99.78	0.27	21.16	15.19	9.48	13.43
Children	59.45	27.81	16.82	19.36	0.21	2.53	29.32	22.30	5.81	11.85
Other family	13.57	21.64	9.80	16.18	0.00	0.00	10.76	16.59	1.80	6.86
Friends	3.92	9.75	63.07	22.21	0.01	0.28	12.00	18.79	1.36	6.08
Others	0.17	1.64	0.49	2.80	0.00	0.00	35.62	11.16	88.50	15.06
5 km proximity	60.80	34.82	57.28	35.22	99.50	6.72	64.44	28.99	81.56	31.29
Daily contact	53.10	35.19	27.58	29.45	99.60	5.66	35.39	29.24	38.82	42.20
Very close	91.39	21.30	75.75	31.56	99.33	23.02	72.42	29.47	57.83	42.69
Network size	2.92	1.39	3.37	1.75	1.04	0.28	3.73	1.36	2.31	1.59

Note: Means for criterion variables express percentages of people classified in that category considering the total size of the network.

category that make up their network and the average percentage of individuals within the network with whom the participant lives 5 km from, has daily contact with and is emotionally close to.

The largest group, labeled as family, consists primarily of children (*M*= 59.45, *SD*= 27.81), spouse (*M*= 30.54, *SD*= 15.51), and other family members (*M*= 13.57, *SD*= 21.64). This profile shows high means of proximity, daily contact, and emotional closeness. The second largest profile is the friends' network, characterized by having most of their support network composed of friends (*M*= 63.07, *SD*= 22.21). This group presents high average levels of emotional closeness and lower average levels of contact and proximity. The profile labeled spouse is mainly composed of the respondent's wife or husband (*M*= 99.78, *SD*= 0.27), with very high means of proximity, contact, and emotional closeness. Individuals within the diverse group present a diverse network composition and a large social network size of confidants. Average proximity, daily contact, and emotional closeness with their network are like that of the friends and family groups. The others network is mostly comprised by neighbors, former colleagues, and formal helpers (*M*= 88.50, *SD*= 15.06) and presents high average levels of proximity but lower average levels of emotional closeness and daily contact.

In its part, sociodemographic characteristics of each profile, together with descriptive information regarding pandemic-specific and mental health variables can be consulted at Table 3.

Data shows a higher proportion of women in all profiles, except in the no network profile. The no network profile presents vulnerable sociodemographic conditions: a high proportion of people with mobility limitations and high average age, economic difficulties, and limited education. In the case of the other profile, most of the individuals within this profile report living alone. For COVID-19-related variables, 14.7% of individuals within the friends' profile report having had or knowing someone who had COVID-19 symptoms, 8.4% of them had or someone close to them had COVID-19, 4.9% were hospitalized or had someone close to them hospitalized due to COVID-19, and 3.9% report that a person that was close to them died due to COVID-19. In general lines, profiles with a small average network size (spouse, other, and no network) report a low incidence of COVID-19 related variables. For mental health variables, more than one third of participants within the no network profile report feeling depressed (35.6%), anxious (35.3%) or lonely (44.8%). Around one from five participants within the friend and diverse profiles state greater feelings of anxiety after COVID-19, and 15.3% of participants in the friends and others profiles report feeling were lonelier after the pandemic began.

Mental health during the first months of COVID

Table 4 presents the results of the multilevel logistic regression analyses for mental health outcomes during COVID-19. Regressions have been applied both to the general question regarding whether the participants had been feeling depressed, anxious, or lonely within the last

Table 3
Social network types by sociodemographic conditions and mental health.

	Family 14,681 (57.5)	Friends 4128 (16.2)	Spouse 3556 (13.9)	Diverse 1732 (8.5)	Others 447 (1.8)	No network 990 (3.9)
	M ± SD					
Education	2.83 ± 1.46	3.22 ± 1.47	2.83 ± 1.43	2.93 ±1.42	2.73 ± 1.42	2.55 ± 1.48
Age	74.84 ± 7.03	73.48 ± 6.36	73.73 ± 6.57	75.31 ± 7.01	76.32 ± 6.94	77.58 ± 7.90
Ends meet	2.77 ± 0.99	2.94 ± 0.98	2.71 ± 0.99	2.86 ± 0.99	2.56 ± 1.01	2.46 ± 1.00
	n (%)					
Women	8764 (59.7)	2692 (65.2)	1211 (65.9)	1095 (63.2)	279 (62.4)	552 (44.2)
Mobility limited	7802 (53.2)	2015 (51.1)	1807 (50.9)	943 (54.5)	627 (59.4)	265 (64.0)
Ends meet great difficulty	1221 (12.3)	277 (9.2)	247 (12.5)	135 (10.4)	65 (18.2)	123 (19.2)
some difficulty	2705 (27.2)	719 (23.8)	592 (30.1)	338 (26.1)	101 (28.2)	220 (34.3)
fairly easily	3168 (31.9)	949 (31.4)	619 (31.4)	339 (30.9)	120 (33.5)	178 (27.7)
easily	2852 (28.7)	1077 (35.6)	511 (26.0)	421 (32.6)	72 (20.1)	121 (18.8)
Live alone	4145 (28.2)	1788 (43.3)	189 (5.3)	752 (43.3)	268 (60.0)	455 (46.0)
Moved from usual house	243 (1.7)	81 (2.0)	59 (1.7)	32 (1.8)	9 (2.0)	36 (3.6)
Had COVID-19 symptoms	1436 (9.8)	602 (14.7)	243 (6.9)	205 (11.9)	29 (6.5)	63 (6.5)
Had COVID-19	898 (6.2)	345 (8.4)	169 (4.8)	105 (6.1)	20 (4.5)	35 (3.6)
Hospitalized COVID-19	428 (2.9)	200 (4.9)	89 (2.5)	55 (3.2)	6 (1.3)	21 (2.1)
Died due to COVID-19	328 (2.2)	161 (3.9)	72 (2.0)	41 (2.4)	9 (2.0)	15 (1.5)
Depressed	3916 (26.8)	1132 (27.5)	766 (21.6)	497 (28.7)	131 (29.3)	342 (35.6)
Anxious	4270 (29.2)	1158 (28.1)	951 (26.8)	527 (30.5)	127 (28.5)	339 (35.3)
Lonely	4548 (31.1)	1336 (32.4)	824 (23.3)	609 (35.2)	198 (44.6)	411 (44.8)
More depressed	2458 (16.8)	740 (18.0)	435 (12.3)	308 (17.8)	67 (15.0)	177 (18.4)
More anxious	3051 (20.9)	869 (21.1)	608 (17.1)	372 (21.5)	86 (19.3)	199 (20.7)
Lonelier	1887 (12.9)	631 (15.3)	315 (8.9)	244 (14.1)	68 (15.3)	131 (14.3)

Table 4
Sociodemographic and social network profiles predictors of mental health during the COVID-19 pandemic.

	Depressed	Anxious	Lonely	More Depressed	More Anxious	Lonelier
Within-level: Country						
Intercept	**2.58*****	**1.28*****	**3.15*****	**2.57*****	**1.47*****	**3.54*****
Variance	**0.11*****	**0.14****	**0.17****	**0.16*****	**0.17****	**0.24*****
Between-level						
Profiles (Ref. = No network)						
Others	0.83	0.91	0.94	0.89	1.20	1.36
Diverse	0.99	1.10	0.93	1.27	**1.39***	**1.46***
Spouse	**0.71****	0.87	**0.71****	0.78	1.02	1.09
Family	**0.84***	0.93	**0.81***	1.07	1.18	1.27
Friends	0.92	0.97	0.83	1.23	1.30	**1.44****
Age	**1.02*****	1.00	**1.03*****	1.01	0.99	**1.01****
Gender (Ref. = Women)	**0.52*****	**0.59*****	**0.66*****	**0.52*****	**0.59*****	**0.56*****
Education	0.99	0.99	0.97	1.01	1.02	1.02
Ends meet (Ref. = Easily)						
Fairly easily	**1.14****	1.09	**1.15****	**1.11***	1.05	1.05
Some difficulty	**1.53*****	**1.23****	**1.37*****	**1.44*****	**1.19****	1.18
Great difficulty	**1.85*****	**1.44*****	**1.64*****	**1.67*****	**1.31*****	**1.38****
Mobility limited	**1.55*****	**1.48*****	**1.41*****	**1.41*****	**1.33*****	**1.22*****
Living alone	**1.33*****	0.95	**3.40*****	**1.17****	0.95	**2.25*****
Had Covid-19 symptoms	**1.19***	**1.32*****	0.973	**1.26****	**1.44*****	1.09
Had Covid-19	0.98	0.90	1.023	1.00	0.93	1.12
Hospitalized Covid-19	1.03	**1.22***	1.076	1.03	1.22	0.99
Died due to the Covid-19	**1.51*****	**1.29***	0.816	**1.61*****	1.22	1.00
N	16,855	16,867	16,823	16,855	16,867	16,823

Note: Full results from logistic regression models. Values presented are ORs, *p<0.05, **p<0.01, ***p<0.001. Had COVID-19 symptoms=Since the outbreak of Corona, did you or anyone close to you experience symptoms that you would attribute to the Covid illness?", Had COVID-19= "Have you or anyone close to you been tested for the Corona virus and the result was positive?"; Hospitalized due to COVID-19= "Have you or anyone close to you been hospitalized due to an infection from the Corona virus?", Died due to COVID-19= "Has anyone close to you died due to an infection from the Corona virus?".

month (Depressed, Anxious, Lonely), and to the specific questions regarding whether these feelings had been greater than before the COVID-19 pandemic (More depressed, More Anxious, Lonelier).

Country was included as a between-level variable with random intercept. The average value of the intercept across countries can be consulted in Table 4 for each model. In each case the between-level variance was statistically significant ($p<.05$), which indicates cross-country variability. Regarding within-level variables, results showed that participants in the spouse profile were more protected against depression, and people in the spouse and familial networks against loneliness during COVID-19. People without social network are 1.41 times more likely (OR=0.71, 95%CI [0.57, 0.88], p=0.002) to experience depression during the pandemic compared to the people in the "spouse" group. and 1.19 times more likely (OR=0.84, 95%CI [0.73, 0.98], p=0.024) than individuals in the "family" group. Also, the results show that participants without a social network are 1.23 (OR=0.81, 95%CI [0.67, 0.98], p=0.034) and 1.40 (OR=0.71, 95%CI [0.58, 0.87], p=0.001) times more likely to experience loneliness during the pandemic compared to those within the familial or spouse networks. However, we did not find statistically significant differences in the levels of depression, anxiety, and loneliness during the pandemic of those with a diverse or friends network compared to the people in the no- network group.

When we examined whether feelings of depression, anxiety and loneliness were greater after the outbreak of the pandemic, results change. The spouse and family profiles were not protective, and individuals within the friends and diverse profiles were more likely to feel enhanced feelings of anxiety or loneliness during the pandemic compared to their previous status than the no network profile. The diverse group is 1.39 (OR=1.39, 95%CI [1.04, 1.84], p= 0.025) times more likely to have felt more anxious and 1.46 (OR=1.46, 95%CI [1.01, 2.11], p= 0.043) times more likely to have suffered lonelier during the pandemic, compared to their previous status, than the no network profile. Also, in comparison to the no network group, the friends' network was 1.44 (OR=1.44, 95%CI [1.11, 1.86], p= 0.007) times more likely to report feeling lonelier during the pandemic than before.

Regarding the control variables, female gender, mobility limitations and having economic great difficulties were statistically significant predictors of likelihood higher probability of experiencing mental health problems during COVID-19. Living alone indicates a higher likelihood of feeling lonely (OR=3.40, 95%CI [2.93, 3.94], $p<0.001$), and lonelier (OR=2.25, 95%CI [1.97, 2.56], $p<0.001$) than before the pandemic. Also, having COVID-19 symptoms or people close that have symptoms seems to increase the likelihood of feeling depressed and anxious, and more depressed and more anxious during the pandemic, compared to their previous status. Lastly, having people close that died due to the COVID-19 is a statistically significant predictor of having higher likelihood of feeling depressed and anxious, as well as reporting feeling more depressed during the pandemic than before.

Discussion

This study identified the five social network profiles labeled as family, friends, spouse, diverse and others, as previous research (Litwin, 2001; Litwin and Stoeckel, 2014). Results reported that social network profiles were associated with mental health outcomes during the COVID-19. More specifically, people in the spouse and family profiles had lower likelihood of feeling depressed or lonely during the COVID-19 in comparison with people without a social network. These results are in line with previous studies (Cheng, 2009; Torres et al., 2023) that support the idea that traditional bonds such as family and having a partner were very important in maintaining mental health before and during the COVID-19 pandemic (Arpino et al., 2022; Li et al., 2021).

However, when we considered whether feelings of depression, anxiety, and loneliness were greater than before the COVID-19 pandemic, our findings differed from previous research. For example, Li et al. (2021) emphasized the role of family support in preserving the mental health of older adults during the pandemic, but our results showed that individuals within the family profile reported feeling as much more depressed, anxious, and lonely during COVID-19 as individuals within the no network profile. A possible explanation for these contrasting results lies in the dynamics of larger family structures. While family can often provide important support, the COVID-19 pandemic may have transformed these larger family units into sources of concern and stress

(Yan et al., 2021). Our study examined the nature of family networks in more detail, revealing that the family network consists not only of close relatives like children and spouses, but also of a notable percentage of other relatives. This idea is in line with the findings of Zhou and Guo (2021), who conducted a large survey in China during the COVID-19 and found that individuals living in large family setups were more likely to experience greater worry and anxiety about COVID-19. Our results also rule out the possibility that the no network group was more predisposed to a deterioration of their mental health after the onset of COVID-19 due to their socio-demographic characteristics, such as living alone, having limited mobility, or facing economic difficulties (Berniell et al., 2021a, 2021b), as all these socio-demographic factors are controlled for in our models.

Furthermore, the diverse profile showed a higher likelihood of experiencing more anxiety during the COVID-19 in comparison to the no network profile. One plausible explanation for these results is rooted in the concept of risk perception. Individuals with more extensive and diverse social networks may indeed face an elevated risk of exposure to the virus. The diverse profile had an expansive network that included individuals from various backgrounds, (spouse, children, other family members, friends, neighbors, former colleagues, and formal helpers), increasing the likelihood of encountering people who have been directly affected by COVID-19. This heightened risk perception is consistent with the findings of Coleman et al. (2022), who found that older adults with broader social networks have higher levels of concern about COVID-19 due to the increased risk of exposure.

In addition, general studies suggest that having a social network that is mainly composed by friends or by diverse acquaintances may be protective for the individual's mental health (Fiori et al., 2006; Litwin and Shiovitz-Ezra, 2011; Park et al., 2018; Torres et al., 2023). Be that as it may, our results showed that during the COVID-19, older adults with diverse and friend network profiles experienced similar levels of depression, anxiety, and loneliness to those with no network, and these networks had a higher likelihood of reporting increased feelings of loneliness during the pandemic than before compared to individuals within the no network group. A possible explanation is that the pandemic increased the difficulties of people in these profiles to maintain contact with people in their social network. The Covid-19 restrictions were especially hard for older adults whose social interaction typically occurred outside their homes, as they were more likely to lack social support during the pandemic (Armitage and Nellums, 2020). The diverse and friends' profiles have high percentages of people living alone, and the frequency of daily contact with their network members is relatively low. This seems to indicate that the diverse and friends' profiles have most of their contact with network members in a context outside the home. Not surprisingly, results regarding increased feelings of loneliness during the pandemic display higher likelihoods of the diverse, and friends' profiles compared to the no network group. In this line, a study by Bundy et al. (2021) showed that older adults who were socially isolated and experienced persistent loneliness prior to the pandemic did not experience a significant increase in loneliness after the outbreak of COVID-19. Therefore, the no network profile may have not experienced higher levels of loneliness during COVID-19 than they already had.

This study has several implications. First, this study highlights the complexity of the social network typologies and how they differently impact mental health outcomes depending on the context. For example, our findings suggest that the dynamics of social networks can change in response to external factors like the COVID-19 pandemic. Traditional sources of support, such as diverse and friends, may not provide the same level of mental health protection during crises. Moreover, understanding the diverse nature of social networks among older people can help adapt support programs considering the specific needs of different network profiles during crises like the COVID-19 pandemic. For example, individuals in the diverse and friends network profiles, who may have faced difficulties maintaining contact with their networks due to COVID-19 restrictions, may benefit from support programs promoting remote social engagement to reduce feelings of loneliness. Also, the pandemic has showed us the importance of maintaining strong social. Future studies should address how to encourage older people to keep in touch with their social network members to mitigate the possible negative mental health outcomes during situations of crisis.

Strengths of this study include the use of data from a large harmonized longitudinal panel study and the methodology employed. We made no a priori assumptions about the types of relationships that are most important to older adults since we used a name-based method (where each participant chose the seven most important people in their social network).

This study also has some limitations. First, the selection of participants from waves 8 and Corona Survey 1 may have induced selection bias since the COVID-19 interview had lower participation rates than a regular SHARE interview. Second, the social network composition is taken from wave 8, so changes in the support networks between the two time-points may have occurred. However, both measurements were very close in time and there is evidence that the size and structure of older adults' social networks are stable over time (Cornwell et al., 2021). In addition, restrictions probably reduced the opportunities to create new ties, forcing people to focus exclusively on the close social networks they had before COVID-19 (Völker, 2023). Fourth, there are some relevant variables that were not included in the study, as for example the prior levels of loneliness, depression, and anxiety, since not all these measures were available at the first measurement-point considered in the study. Moreover, this study could not account for other variables of interest, such as the type of contact (face-to-face or online), which could impact older adults' mental health during the COVID-19 pandemic (Litwin and Levinsky, 2021). Finally, our study considered the effect of country as a between-level variable, but we did not explore potential differences among countries. Future studies could address this question since European countries had different strategies to control the pandemic (Engler et al., 2021) and present notable differences in the prevalence of the social networks (Torres et al., 2023).

Conclusions

This study provides some insights into the role of social networks in protecting mental health during the COVID-19 pandemic among older adults. Our results showed that the protective role of some social networks for the mental health of the older adults may change in situations such as the COVID-19 pandemic. This study highlights the vulnerability of the diverse and friends profiles in this extraordinary situation, in contrast to their association to good mental health outcomes before the pandemic, as previously reported in the literature. Identifying those individuals who are particularly vulnerable in each situation and determining the type of support they may require is critical. Even though the COVID-19 pandemic was a unique situation, knowing the characteristics of the social network typologies and their role in protecting mental health can help us to be prepared for future situations.

Funding

This research is framed in project PID2021-124418OB-I00 "Successful Aging in Europe: Trajectories and Processes to Act on psychological, social and physical frailty (SAETA)" funded by MCIN/AEI/10.13039/501100011033 and by "ERDF A way of making Europe". Zaira Torres is a researcher beneficiary of the FPU program from the Spanish Ministry of Universities (FPU20/02482) and of the complementary mobility grant for FPU beneficiaries (EST23/00329).

CRediT authorship contribution statement

Irene Fernández: Data curation, Formal analysis, Methodology, Supervision, Writing – review & editing. **Amparo Oliver:**

Conceptualization, Funding acquisition, Project administration, Supervision, Writing – review & editing. **Zaira Torres:** Conceptualization, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare no actual or potential conflicts of interest related to this study.

Data availability

The data that support the findings of this study are available at the SHARE Research Data Center to the entire research community free of charge (www.share-project.org). Restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are however available from the authors upon reasonable request and with permission of the SHARE Project (http://www.share-project.org/data-access/user-registration.html?L=).

Acknowledgments

This paper uses data from SHARE Wave 8 and 8 COVID-19 (DOIs: 10.6103/SHARE.w8.800, 10.6103/SHARE.w8ca.800) see Börsch-Supan et al. (2013) for methodological details. The SHARE data collection has been funded by the European Commission, DG RTD through FP5 (QLK6-CT-2001–00360), FP6 (SHARE-I3: RII-CT-2006–062193, COMPARE: CIT5-CT-2005–028857, SHARELIFE: CIT4-CT-2006–028812), FP7 (SHARE-PREP: GA N°211909, SHARE-LEAP: GA N°227822, SHARE M4: GA N°261982, DASISH: GA N°283646) and Horizon 2020 (SHARE-DEV3: GA N°676536, SHARE-COHESION: GA N°870628, SERISS: GA N°654221, SSHOC: GA N°823782, SHARE-COVID19: GA N°101015924) and by DG Employment, Social Affairs & Inclusion through VS 2015/0195, VS 2016/0135, VS 2018/0285, VS 2019/0332, and VS 2020/0313. Additional funding from the German Ministry of Education and Research, the Max Planck Society for the Advancement of Science, the U. S. National Institute on Aging (U01_AG09740–13S2, P01_AG005842, P01_AG08291, P30_AG12815, R21_AG025169, Y1-AG-4553–01, IAG_BSR06–11, OGHA_04–064, HHSN271201300071C, RAG052527A) and from various national funding sources is gratefully acknowledged (see www.share-project.org).

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.socnet.2024.02.003.

References

Antonucci, T.C., 1986. Measuring social support networks: hierarchical mapping technique. Gener. J. Am. Soc. Aging *10* (4), 10–12.
Antonucci, T.C., Ajrouch, K.J., Birditt, K.S., 2014. The convoy model: explaining social relations from a multidisciplinary perspective. Gerontologist *54* (1), 82–92. https://doi.org/10.1093/geront/gnt118.
Armitage, R., Nellums, L.B., 2020. COVID-19 and the consequences of isolating the elderly. Lancet Public Health *5* (5), e256. https://doi.org/10.1016/S2468-2667(20)30061-X.
Arpino, B., Mair, C.A., Quashie, N.T., Antczak, R., 2022. Loneliness before and during the COVID-19 pandemic—are unpartnered and childless older adults at higher risk? Eur. J. Ageing *19* (4), 1327–1338. https://doi.org/10.1007/s10433-022-00718-x.
Atzendorf, J., Gruber, S., 2021. Depression and loneliness of older adults in Europe and Israel after the first wave of covid-19. Eur. J. Ageing *1*, 1–13. https://doi.org/10.1007/S10433-021-00640-8.
Bergmann, M., Börsch-Supan, A. (Eds.), 2021. SHARE Wave 8 Methodology: Collecting Cross-National Survey Data in Times of COVID-19. Munich: MEA, Max Planck Institute for Social Law and Social Policy.
Berniell, I., Laferrère, A., Mira, P., Pronkina, E., 2021a. Robinson Crusoe: Less or More Depressed? With Whom and Where to Live in a Pandemic If You are above 50 about the SHARE Working Paper Series. 870628. https://doi.org/10.17617/2.3333206.
Berniell, I., Laferrère, A., Mira, P., Pronkina, E., 2021b. SHARE Working Paper Series 70-2021: Robinson Crusoe: Less or More Depressed? With Whom and Where to Live in a Pandemic If You are Above 50. SHARE-ERIC, Munich. https://doi.org/10.17617/2.2333206.
Bethmann, A., Bergmann, M., Scherpenzeel, A., 2019. SHARE Sampling Guide – Wave 8. Working Paper Series 33-2019.
Börsch-Supan, A., 2022a. Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8. Release version: 8.0.0. SHARE-ERIC. Data set. https://doi.org/10.6103/SHARE.w8.800.
Börsch-Supan, A., 2022b. Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8. COVID-19 Survey 1. Release version: 8.0.0. SHARE-ERIC. Data set. https://doi.org/10.6103/SHARE.w8ca.800.
Bundy, H., Lee, H.M., Sturkey, K.N., Caprio, A.J., 2021. The lived experience of already-lonely older adults during COVID-19. Gerontologist *61* (6), 870–877. https://doi.org/10.1093/geront/gnab078.
Cheng, S.T., Lee, C.K.L., Chan, A.C.M., Leung, E.M.F., Lee, J.J., 2009. Social network types and subjective well-being in Chinese older adults. J. Gerontol. Ser. B Psychol. Sci. Soc. Sci. *64* (6), 713–722. https://doi.org/10.1093/geronb/gbp075.
Choi, E.Y., Farina, M.P., Wu, Q., Ailshire, J., 2022. COVID-19 Social distancing measures and loneliness among older adults. J. Gerontol. Ser. B Psychol. Sci. Soc. Sci. *77* (7), E167–E178. https://doi.org/10.1093/geronb/gbab009.
Cohn-Schwartz, E., Levinsky, M., Litwin, H., 2021. Social network type and subsequent cognitive health among older Europeans. Int. Psychogeriatr. *33* (5), 495–504. https://doi.org/10.1017/S1041610220003439.
Coleman, M.E., Manchella, M.K., Roth, A.R., Peng, S., Perry, B.L., 2022. What kinds of social networks protect older adults' health during a pandemic? The tradeoff between preventing infection and promoting mental health. Soc. Netw. *70*, 393–402. https://doi.org/10.1016/j.socnet.2022.05.004.
Cornwell, B., Goldman, A., Laumann, E.O., 2021. Homeostasis revisited: patterns of stability and rebalancing in older adults' social lives. J. Gerontol. Ser. B Psychol. Sci. Soc. Sci. *76* (4), 778–789. https://doi.org/10.1093/geronb/gbaa026.
Engler, S., Brunner, P., Loviat, R., Abou-Chadi, T., Leemann, L., Glaser, A., Kübler, D., 2021. Democracy in times of the pandemic: explaining the variation of COVID-19 policies across European democracies. West Eur. Polit. *44* (5–6), 1077–1102. https://doi.org/10.1080/01402382.2021.1900669.
Ferguson, S.L., G. Moore, E.W., Hull, D.M., 2020. Finding latent groups in observed data: a primer on latent profile analysis in Mplus for applied researchers. Int. J. Behav. Dev. *44* (5), 458–468. https://doi.org/10.1177/01650254198817.
Fernandes, A.A.T., Filho, D.B.F., da Rocha, E.C., da Silva Nascimento, W., 2020. Read this paper if you want to learn logistic regression. Rev. Sociol. Polit. *28* (74) https://doi.org/10.1590/1678-987320287406EN.
Fiori, K.L., Antonucci, T.C., Akiyama, H., 2008. Profiles of social relations among older adults: a cross-cultural approach. Ageing Soc. *28* (2), 203–231. https://doi.org/10.1017/S0144686×07006472.
Fiori, K.L., Antonucci, T.C., Cortina, K.S., 2006. Social network typologies and mental health among older adults. J. Gerontol. Ser. B Psychol. Sci. Soc. Sci. *61* (1), 25–32. https://doi.org/10.1093/geronb/ 61.1.P25.
Harasemiw, O., Newall, N., Mackenzie, C.S., Shooshtari, S., Menec, V., 2019. Is the association between social network types, depressive symptoms and life satisfaction mediated by the perceived availability of social support? A cross-sectional analysis using the Canadian longitudinal study on aging. Aging Ment. Health *23* (10), 1413–1422. https://doi.org/10.1080/13607863.2018.1495176.
Kovacs, B., Caplan, N., Grob, S., King, M., 2021. Social Networks and Loneliness During the COVID-19 Pandemic. Socius 7. https://doi.org/10.1177/2378023120985254.
Krendl, A.C., Perry, B.L., 2021. The impact of sheltering in place during the COVID-19 pandemic on older adults' social and mental well-being. J. Gerontol. Ser. B *76* (2), e53–e58. https://doi.org/10.1093/geronb/gbaa110.
Lau, Y.W., Vaingankar, J.A., Abdin, E., Shafie, S., Jeyagurunathan, A., Zhang, Y., Magadi, H., Ng, L.L., Chong, S.A., Sub- ramaniam, M., 2019. Social support network typologies and their association with dementia and depression among older adults in Singapore: a cross-sectional analysis. Article e025303 BMJ Open *9* (5). https://doi.org/10.1136/bmjopen-2018-025303.
Lestari, S.K., Eriksson, M., de Luna, X., Malmberg, G., Ng, N., 2022. Frailty and types of social relationships among older adults in 17 European countries: a latent class analysis. Arch. Gerontol. Geriatr. *101*, 104705 https://doi.org/10.1016/j.archger.2022.104705.
Li, F., Luo, S., Mu, W., Li, Y., Ye, L., Zheng, X., Xu, B., Ding, Y., Ling, P., Zhou, M., Chen, X., 2021. Effects of sources of social support and resilience on the mental health of different age groups during the COVID-19 pandemic. BMC Psychiatry *21* (1), 1–15. https://doi.org/10.1186/s12888-020-03012-1.
Litwin, H., 2001. Social network type and morale in old age. Gerontologist *41* (4), 516–524. https://doi.org/10.1093/geront/41.4.516.
Litwin, H. (Ed.), 1996. The Social Networks of Older People: A Cross-National Analysis. Westport, CT: Praeger.
Litwin, H., Levinsky, M., 2021. Social networks and mental health change in older adults after the Covid-19 outbreak. Aging Ment. Health *26* (5), 925–931. https://doi.org/10.1080/13607863.2021.1902468.
Litwin, H., Shiovitz-Ezra, S., 2011. Social network type and subjective well-being in a national sample of older Americans. Gerontologist *51* (3), 379–388. https://doi.org/10.1093/geront/gnq094.
Litwin, H., Stoeckel, K.J., 2014. Confidant network types and well-being among older Europeans. Gerontologist *54* (5), 762–772. https://doi.org/10.1093/geront/gnt056.
Lo, Y., Mendell, N., Rubin, D., 2001. Testing the number of components in a normal mixture. Biometrika *88* (3), 767–778. https://doi.org/10.1093/biomet/88.3.767.
Lüdecke, D., von dem Knesebeck, O., 2022. Decline in mental health in the beginning of the COVID-19 outbreak among European older adults—associations with social

factors, infection rates, and government response. Front. Public Health *10* (March), 1–10. https://doi.org/10.3389/fpubh.2022.844560.
Lukočienė, O., Varriale, R., Vermunt, J.K., 2010. The simultaneous decision (s) about the number of lower-and higher-level classes in multilevel latent class analysis. Sociol. Methodol. *40* (1), 247–283. https://doi.org/10.1111/j.1467-9531.2010.01231.x.
Magidson, J., Vermunt, J., 2002. Latent class models for clustering: a comparison with K-means. Can. J. Mark. Res. 20 (1), 36–43.
Marsh, H.W., Lüdtke, O., Trautwein, U., Morin, A.J., 2009. Classical latent profile analysis of academic self-concept dimensions: synergy of person and variable-centered approaches to theoretical models of self-concept. Struct. Equ. Model. *16*, 191–225. https://doi.org/10.1080/10705510902751010.
Masyn, K.E., 2013. Latent class analysis and finite mixture modeling. In: Little, T. (Ed.), The Oxford Handbook of Quantitative Methods. Oxford University Press, New York, NY, pp. 551–611.
Maxfield, M., Pituch, K.A., 2020. COVID-19 worry, mental health indicators, and preparedness for future care needs across the adult lifespan. Aging Ment. Health *25* (7), 1273–1280. https://doi.org/10.1080/13607863.2020.1828272.
McLachlan, G., Peel, D., 2000. Finite Mixture Models. Wiley.
Medvene, L.J., Nilsen, K.M., Smith, R., Ofei-Dodoo, S., DiLollo, A., Webster, N., Graham, A., Nance, A., 2016. Social networks and links to isolation and loneliness among elderly HCBS clients. Aging Ment. Health *20* (5), 485–493. https://doi.org/10.1080/13607863.2015.1011080.
Mendez-Lopez, A., Stuckler, D., McKee, M., Semenza, J.C., Lazarus, J.V., 2022. The mental health crisis during the COVID-19 pandemic in older adults and the role of physical distancing interventions and social protection measures in 26 European countries. SSM Popul. Health *17* (August 2021), 101017. https://doi.org/10.1016/j.ssmph.2021.101017.
Muthén, L.K., Muthén, B.O., 1998–2017. Mplus User's Guide (8th ed.). Muthén & Muthén.
Nylund, K.L., Asparouhov, T., Muthén, B.O., 2007. Deciding on the number of classes in latent class analysis and growth mixture modeling: a Monte Carlo simulation study. Struct. Equ. Model. *14* (4), 535–569. https://doi.org/10.1080/10705510701575396.
Park, N.S., Jang, Y., Lee, B.S., Chiriboga, D.A., Chang, S., Kim, S.Y., 2018. Associations of a social network typology with physical and mental health risks among older adults in South Korea. Aging Ment. Health 22 (5), 631–638. https://doi.org/10.1080/13607863.2017.1286456.
Park, N.S., Jang, Y., Lee, B.S., Ko, J.E., Haley, W.E., Chiriboga, D.A., 2015. An empirical typology of social networks and its association with physical and mental health: a study with older Korean immigrants. J. Gerontol. Ser. B Psychol. Sci. Soc. Sci. *70* (1), 67–76.
Plümper, T., Neumayer, E., 2022. The politics of covid-19 containment policies in Europe. Int. J. Disaster Risk Reduct. *81*, 103206 https://doi.org/10.1016/j.ijdrr.2022.103206.
Posch, M., Bauer, P., Posch, A., Konig, F., 2020. Analysis of Austrian COVID-19 deaths by age and sex. Wien. Klin. Wochenschr. 132, 685–689. https://doi.org/10.1007/s00508-020-01707-9.
Prince, M.J., Reischies, F., Beekman, A.T.F., Fuhrer, R., Jonker, C., Kivela, S.L., Lawlor, B.A., Lobo, A., Magnusson, H., Fichter, M., Van Oyen, H., Roelands, M., Skoog, I., Turrina, C., Copeland, J.R.M., 1999. Development of the EURO-D scale – a European Union initiative to compare symptoms of depression in 14 European centres. Br. J. Psychiatry *174*, 330–338.
Scheel-Hincke, L.L., Ahrenfeldt, L.J., Andersen-Ranberg, K., 2021. Sex differences in activity and health changes following COVID-19 in Europe-results from the SHARE COVID-19 survey. Eur. J. Public Health *31* (6), 1281–1284. https://doi.org/10.1093/eurpub/ckab096.
Scherpenzeel, A., Axt, K., Bergmann, M., Douhou, S., Oepen, A., Sand, G., Schuller, K., Stuck, S., Wagner, M., Börsch-Supan, A., 2020. Collecting survey data among the 50 + population during the COVID-19 outbreak: the Survey of Health, Ageing and Retirement in Europe (SHARE). Surv. Res. Methods *14* (2), 217–221.
Shevlin, M., McBride, O., Murphy, J., Miller, J., Hartman, T., Levita, L., Bentall, R., 2020. Anxiety, depression, traumatic stress and COVID-19-related anxiety in the UK general population during the COVID-19 pandemic. E125 BJPsych Open *6* (6). https://doi.org/10.1192/bjo.2020.109.
Skałacka, K., Pajestka, G., 2021. Digital or In-Person: the relationship between mode of interpersonal communication during the COVID-19 pandemic and mental health in older adults from 27 Countries. J. Fam. Nurs. *27* (4), 275–284. https://doi.org/10.1177/10748407211031980.
Steinley, D., 2003. Local optima in K-means clustering what you don't know may hurt you. Psychol. Methods *8* (3), 294. https://doi.org/10.1037/1082-989x.8.3.294.
Steptoe, A., Di Gessa, G., 2021. Mental health and social interactions of older people with physical disabilities in England during the COVID-19 pandemic: a longitudinal cohort study. Lancet Public Health *6* (6), e365–e373. https://doi.org/10.1016/S2468-2667(21)00069-4.
Tein, J.Y., Coxe, S., Cham, H., 2013. Statistical power to detect the correct number of classes in latent profile analysis. Struct. Equat. Model. Multidiscip. J. *20* (4), 640–657. https://doi.org/10.1080/10705511.2013.824781.
Torres, Z., Oliver, A., Tomás, J.M., 2023. Mapping protective performance of social network types on health and quality of life in older people in European regions. J. Aging Health *35* (7-8), 500–510. https://doi.org/10.1177/08982643221142078.
Van Tilburg, T.G., Steinmetz, S., Stolte, E., Van der Roest, H., de Vries, D.H., 2021. Loneliness and mental health during the COVID-19 pandemic: a study among Dutch older adults. e249-e255 J. Gerontol. Ser. B *76* (7). https://doi.org/10.1093/geronb/gbaa111.
Völker, B., 2023. Networks in lockdown: the consequences of COVID-19 for social relationships and feelings of loneliness. Soc. Netw. *72* (August 2022), 1–12. https://doi.org/10.1016/j.socnet.2022.08.001.
Wenger, G.C., 1991. A network typology: from theory to practice. J. Aging Stud. *5* (2), 147–162. https://doi.org/10.1016/0890-4065(91)90003-B.
Wenger, G.C., 1997. Social networks and the prediction of elderly people at risk. Aging Ment. Health 1, 311–320.
Yan, X., Qu, T., Sperber, N., Lu, J., Fan, M., Cornwell, B., 2021. Tied infections: how social connectedness to other COVID-19 patients influences illness severity. Am. Behav. Sci. *65* (14), 1901–1928.
Ye, L., Zhang, X., 2019. Social network types and health among older adults in Rural China: the mediating role of social support. Int. J. Environ. Res. Public Health *16* (3). https://doi.org/10.3390/ijerph16030410.
Zhou, M., Guo, W., 2021. Social factors and worry associated with COVID-19: evidence from a large survey in China. Soc. Sci. Med. *277*, 113934 https://doi.org/10.1016/j.socscimed.2021.113934.