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Original Research Article

Multidimensional Social Network Types and Their Correlates in Older Americans

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Abstract

Background and Objectives: Social support networks of older adults have been linked to their health and well-being; however, findings regarding the effects of specific network characteristics have been mixed. Additionally, due to demographic shifts increasing numbers of older adults live outside of traditional family structures. Previous studies have not systematically examined the resulting complexity and heterogeneity of older adults' social networks. Our objectives were to examine this complexity and heterogeneity by developing a multidimensional typology of social networks that simultaneously considers multiple structural and functional network characteristics, and to examine differences in network type membership by sociodemographic characteristics, health characteristics, and birth cohort.
Research Design and Methods: Participants included 5,192 adults aged 57–85 years in the National Social Life, Health, and Aging Project at rounds 1 (2005–2006) and 3 (2015–2016). Data were collected on social relationships including network size, diversity, frequency of contact, and perceived support and strain in relationships. We used latent class analysis to derive the network typology and multinomial logistic regression to examine differences in network type membership by sociodemographic characteristics, health characteristics, and birth cohort.
Results: Older adults were classified into 5 distinct social network types: (i) *large, with strain*; (ii) *large, without strain*; (iii) *small, diverse, low contact*; (iv) *small, restricted, high contact*; and (v) *medium size and support*. Membership in these network types varied by age, gender, marital status, race/ethnicity, education, mental health, and birth cohort.
Discussion and Implications: Network typologies can elucidate the varied interpersonal environments of older adults and identify individuals who lack social connectedness on multiple network dimensions and are therefore at a higher risk of social isolation.

Translational Significance: This study examines the complexity and heterogeneity in social networks of older adults using a network typology approach. We found evidence for 5 different network types, each with varying degrees of size, diversity, and perceived social support. Furthermore, membership in network types varied by sociodemographic and health characteristics of older adults. Findings will improve the conditions associated with aging by identifying vulnerable older adults with fewer social resources, and promoting interventions that not only increase the size of one's network but also promote supportive relationships and minimize relationship strain.

Keywords: Network typology, Older adults, Social relationships, Social support, Social strain

Background and Objectives

Networks of social relationships are an important aspect of older adults' well-being, as they shape the nature and frequency of social interactions and provide opportunities for social engagement, support, and exchange of information. In addition, social networks are thought to have physical and health benefits such as reducing the risk of multiple morbidities and premature mortality (1). Despite extensive evidence of the benefits of supportive social networks, the complexity and heterogeneity of older adults' social networks remain poorly understood, which is an important reason for our incomplete understanding of how these networks affect health and well-being in late life. Network typology has been recognized as a useful approach to identifying combinations of structural and functional qualities that characterize the social relationships within a particular individual's network. Although this approach has been applied to investigate the social networks of older adults, prior research has rarely simultaneously considered the confidant network of close ties as well as the larger network of distant family and friends, and has rarely simultaneously considered both support and strain in relationships in the construction of network types. In the present study, we develop a typology of the social networks of a nationally representative sample of older adults using both the confidant network as well as the larger network of family and friend ties and incorporating both social support and strain in relationships. We determine the prevalence of the specific social network configurations in our sample and examine the primary sociodemographic and health-related correlates of these network types. Finally, we also include an exploratory analysis of whether the prevalence of specific network types varies by 2 birth cohorts of older adults.

Structural and Functional Network Characteristics

Features of social networks are broadly categorized into 2 dimensions—structural and functional—which operate through different pathways to affect well-being and health (2). Structural aspects refer to the extent to which individuals are situated within social networks (3). They include objective characteristics of the network such as size (number of relationships), frequency of contact with network members, network diversity (number of different social roles such as family, friends, and neighbors), and geographic proximity of network members (4). Network structure determines the type and quantity of resources available. For instance, having a larger network and more contact with network ties offers access to more resources (5) and more opportunities for social engagement and cognitively stimulating interactions that in turn enhance well-being (6). Similarly, having a diverse network offers more opportunities to compensate for network losses as well as to call on diverse sets of resources in response to specific social, emotional, and health-related needs (7). In this study, we conceptualize network structure in terms of the size of the confidant network, family and friend networks, the diversity in confidant ties, and the frequency of contact with confidants.

Functional aspects of social networks reflect the types of resources that are exchanged between network members and the subjective or emotional quality of relationships (8). Measurement of network function has historically been restricted to actual receipt or exchange of support (9,10). However, opportunities for exchange of support and the perceived availability of support are also considered functional resources (11). In epidemiologic studies, received support is associated with higher mortality rates, whereas perceived support is associated with lower mortality rates (12). This suggests that received support is an indication of an individual's poor health and therefore of need for support rather than availability of support (13). In contrast, perceived support is a measure of how an individual appraises potential support available to them. Perceptions of support can affect one's appraisal of and one's response to a stressful situation, thereby reducing subsequent stress and adverse health consequences, independently of actual support received (14). In the present study, we assess perceived, rather than received, support.

In addition to support, relationships can also be a source of strain, with some evidence suggesting that strain in relationships, such as excessive demands and criticism, have a more substantial impact on health and well-being than support (15,16). Understanding how negative and positive relationship perceptions co-occur is theoretically and practically relevant. Investigating both appraisals simultaneously shows whether and in what pattern they arise (only support or strain, both strain and support, the particular source of support and strain), and the contextual factors associated with supportive versus strained relationships. In this study, we conceptualize network function in terms of perceived support from family and friends, and perceived strain in family relationships and friendships.

Social Network Typologies

Social networks of older adults are characterized by different heterogeneous structural and functional features, making them particularly complex. Because these features and the benefits derived from them are unlikely to be uniform across individuals or networks of the same structure or function, there is considerable heterogeneity in social networks across older individuals. There have been few theoretical frameworks of network typologies that focus on the heterogeneity and complexity of network structures and functions for older adult populations. One exception is the social convoy model, which proposes that each individual is surrounded by a network of supportive social ties—referred to as their social convoy—that provides a protective base for individuals (17,18). The convoy model places network ties into concentric layers of varying levels of emotional closeness with those in the inner layers representing greater emotional closeness. This convoy moves with individuals across time, and reflects transitions and choices made throughout the life course (19). The social convoy model is an example of a framework that took a multidimensional approach to describe the heterogeneity of social networks in older populations (20). According to the convoy model, the structure and function of social relations are fundamental to understanding individuals' physical and mental health (9). Building on this work, in this study we are using a quantitative approach to identify distinct network types in the older adult population in the United States. In doing so, we also want to account for the heterogeneity and complexity of social networks by including multiple elements of network structure, and multiple elements of network function, including social strain.

A network typology approach examines multiple network characteristics simultaneously rather than examining individual network characteristics separately, allowing us to understand the complexity and heterogeneity of social networks of older adults (4,21–23). This approach groups individuals with similar patterns of network characteristics (eg, network size and composition) together. Network typology captures the heterogeneity in not just 1 specific aspect of the social network, such as size, but rather the heterogeneity in the specific combinations of multiple network features that form individuals' social networks (24). The 4 main network types that have been identified based on the structural characteristic of network composition include: *diverse network*, reflecting a variety of relationships across various roles; *family-focused network*, consisting primarily of relatives; *friend-focused network*, consisting primarily of friends; and *restricted network*, a small network with few supportive relationships (21,25–30). Beyond these, other studies in different populations have found additional network types based on additional structural network characteristics. For instance, Litwin and Shiovitz-Ezra using data from Israel identified 2 additional network types, *community-clan* and *neighbor* using dimensions of contact with neighbors and involvement in religious and other group activities (31). Park et al. identified 3 additional types, *unmarried/diverse*, *married/coresidence*, and *unmarried/restricted* using dimensions of marital status and coresidence among community-dwelling older Korean immigrants (29). These studies have been limited in their ability to describe the social networks of older adults because of an exclusive focus on structural network characteristics. Structurally similar networks may be functionally different, and for a more complete assessment of social networks of older adults it is important to consider both structural and functional network characteristics.

A few studies have additionally examined functional network characteristics of received support and emotional closeness (9,32,33). These studies have found additional network types including *friend-focused supported, friend-focused unsupported, functionally restricted* (9); *acquisitive style-low closeness, acquisitive style-high closeness* (32); *large-supportive*, *large-unsupportive*, *small-supportive*, *small-unsupportive* (33). Not only did the inclusion of functional characteristics along with structural characteristics in these studies result in additional network types, but it also showed that networks that appear structurally similar (eg, large in size) may not be functionally similar (eg, large-supportive vs large-unsupportive). These typologies have contributed to the literature by revealing the diversity among social networks of older adults and identifying key dimensions on which relationships of older adults differ; yet, this observation highlights the value of an updated typology that captures a broader spectrum of network characteristics to refine our understanding of these networks of older adults including the broader social network comprised of confidants, family and friend ties, and through simultaneous examination of support and strain experienced in these relationships.

Correlates of Network Types

The social convoy model posits that individual characteristics, such as age and gender, and situational characteristics, such as cultural norms, play an important role in the formation and expression of social relations (26,34,35). Consider, for example, an older retired man. His convoy may consist of fewer peripheral ties such as distant friends and coworkers and more ties with children and other immediate family members. In contrast, the convoy of an older widowed woman recovering from a broken hip may consist primarily of coresiding family members and neighbors who can help her with daily activities and fewer connections with family and friends that are geographically distant. Among individual and situational characteristics, age, sex, race/ethnicity, marital status, education, physical health, and mental health are known correlates of individual network characteristics that may shape both the structure and function of one's network.

Age

An increase in age is generally associated with a decrease in network size, diversity, and reports of social strain, but an increase in reports of social support (4,9); this is also consistent with socioemotional selectivity theory, which posits that with increasing age, adults let go of peripheral ties that are not satisfactory and focus on a few close relationships that are able to provide higher levels of support (36,37). Age and frequency of contact with network members have a U-shaped relationship such that the young–old and the oldest old have been shown to have higher levels of contact with network members; in contrast, the middle-old have less frequent contact with their ties (38).

Gender

Women, compared to men, report having larger confidant networks, greater diversity in their networks, more frequent contact with network members, and greater exchange of support (5,39,40).

Marital status

Married, compared to unmarried, individuals have larger family networks and overall, more diverse networks (41,42).

Race/ethnicity

White older adults report having larger confidant networks (5,39,40). In contrast, Hispanic and Black older adults are more likely to report smaller, more kin-centered networks, and higher frequency of contact with their ties; at the same time, Black older adults also report more negative interactions with their ties compared to White older adults (5,9).

Education

Individuals with more education are known to have larger and more diverse networks, whereas those with less education tend to have smaller and more restricted networks, primarily consisting of family members (9,41).

Chronic conditions

Physical health and social networks are closely related. On the one hand, social relationships can play an important role in preventing and in managing chronic conditions (43). On the other hand, an individual needs to be physically healthy to a certain extent in order to be able to maintain and reciprocate social connections. In fact, individuals with multiple chronic conditions, and therefore worse overall health, tend to have more limited activity spaces which can result in limited social interactions, and smaller and less diverse social networks (44).

Depressive symptoms

Worse mental health, such as higher depressive symptomatology, often includes social withdrawal and a decrease in participation in social activities (45). In contrast to individuals with fewer depressive symptoms, those with more depressive symptoms may have a harder time maintaining larger and diverse networks and more frequent contact with ties (45). The reverse is also possible, as shown by previous studies; individuals with less social support tend to have higher depressive symptomatology (46).

Birth cohort

Sociodemographic and historical shifts in population are likely to fundamentally influence the structure and function of social networks due to the unique situational characteristics they produce. Secular trends in family norms and associated changes in filial obligations have implications for the structure and function of networks. Across subsequent birth cohorts, families have become smaller as birth rates have declined (47). Additionally, adult children of later cohorts are more likely to move away from their parents to pursue educational and economic opportunities, resulting in smaller and less family-focused networks (47). Overall, network diversity has also increased across birth cohorts as acceptance of nontraditional families and nonkin relationships has increased and older adults rely more on their friendship ties for support (48–50). While there has been limited research on cohort differences in individual network characteristics, very little is known about cohort differences in more complex network types (10). In this study, we explore the degree to which the prevalence in network types varies by birth cohort.

Present Study

The aims of the present study are (i) to identify distinguishable social network types in an attempt to understand how structural and functional characteristics uniquely characterize each group, and determine their prevalence in a nationally representative sample of older adults; (ii) to examine how sociodemographic characteristics and health characteristics of older adults vary by social network type; and (iii) to explore differences in network type membership by birth cohort.

This study aims to better understand heterogeneous patterns in social networks of older adults and extends prior research in multiple ways. First, it considers both the confidant network of close ties as well as the larger network of family and friends to obtain social network types. Research on support typologies generally includes ties in the core network, identified using a name generator (24,42,51–53). These studies do not limit the network to a particular relationship type(s) but core confidants usually consist only of the closest ties of an individual, such as those in the innermost circle of the social convoy model, and exclude the larger network of friends and family. Other studies have restricted their measurement of network types to specific relationships such as kin (22,23,25,29,54,55), nonkin (22,23,25,29,32,33), and church networks (23,55). The present study includes both network members from the core network as well as the larger network of friends and family not necessarily identified as close confidants; this approach more accurately reflects interactions within support networks, which are not limited to the core network or to specific relationship types. Availability of distant family and friends can affect one's perceptions of available support and previously distant family and friends may take the place of close family and friends in case of loss of a confidant, making it critical to include both the core network and the larger network of family and friends. Second, in prior network typology research, social support has been measured using indicators of received support (9,23,25,26,33,54–56). In the present study, we use perceived support to operationalize social support because measures of perceived and received support are only moderately correlated and have different associations with health (57). Third, research on network typology rarely includes a measure of strain in relationships, such as criticisms and excessive demands, with the exception of a few studies (9,23,55). The present study includes strain from family and friends in the development of network typologies. Lastly, it explores differences in network typology by birth cohort, which has been done by only 2 other studies to our knowledge (10,58).

Research Design and Methods

Sample and Data Collection

Data for the study came from the National Social Life, Health, and Aging Project (NSHAP). NSHAP is a longitudinal, population-based study of health and social factors, designed to understand the well-being of community-dwelling older Americans. Participants aged 57–85 years at baseline were recruited using a complex, multistage area probability design, with oversampling of Blacks, Hispanics, men, and the oldest old (75–84 years). The study obtained a 75.5% weighted response rate (59). Data collection consisted of a face-to-face interview including a brief self-administered questionnaire, in-home collection of biomeasures, and a leave-behind questionnaire. The first round of data collection took place from 2005 to 2006 (*N* = 3,005). In 2010–2011, 3,400 interviews were completed with round 1 respondents, noninterviewed respondents, and their partners. In 2015–2016, all surviving respondents were reinterviewed and a new cohort of respondents born between 1948 and 1965 was added along with their partners, totaling 4,777 interviews (60,61). The present study used data from 3 005 participants who completed interviews during round 1 and 2,187 respondents from round 3 who were not interviewed in round 1.

Social Network Measures

During the in-home interview and the leave-behind questionnaire, NSHAP collected data on core confidants (alters), who are individuals most important to the respondent (ego), as well as friends and family in the respondent's broader social network. Using questions called *name generators* respondents were asked to identify core confidants with whom they discussed important things over the last 12 months (5). For each confidant identified, additional information was collected including the relationship of the ego with the alter and ego's frequency of contact with the alter. Additionally, NSHAP collected data on the respondents' broader network of family and friends, including the respondent's perception of support available from family and friends, and any strain experienced in these relationships.

Network types were derived through the application of latent class analysis (LCA) using 9 observed variables that reflect both structural and functional components of the social network. Table 1 provides a description of each of the network characteristics including the specific questions and response categories used to measure each variable. These included 5 items representing structural aspects: number of core confidants, number of family members, and number of friends as measures of network size, network diversity in confidants, and frequency of contact with confidants; and 4 items representing functional aspects: social support from family, social support from friends, strain in relationships with family, and strain in relationships with friends. Depending on how the question was asked, responses were averaged either across all confidants or across broad relationships categories (family, friends) for each respondent, to obtain the overall score for each network characteristic. The overall score for each network characteristic was then categorized into 2 or 3 levels based on the variable's distribution.

Correlates of Network Types

Sociodemographic characteristics

We included a number of sociodemographic characteristics, including age (in years), sex (male, female), whether the respondent was married or living with a partner (yes, no), race/ethnicity (White; Black; Other), and education (high school or less; vocational certificate/some college/Associate's degree; Bachelor's or more).

Chronic conditions

NSHAP participants were asked whether a doctor had ever told them that they had any of the following 9 conditions: arthritis, asthma/emphysema, cancer, congestive heart failure, mild cognitive impairment or dementia, diabetes, hypertension, myocardial infarction, and stroke. We created a summed score of chronic conditions, which ranged from 0 to 8, as no one reported all 9 conditions. We restricted the analysis to those conditions for which data were collected in both rounds 1 and 3. For the multivariable multinomial logistic regression model, we recoded the number of chronic conditions as an ordinal variable (0 conditions, 1 condition, 2 conditions, or 3 or more conditions) given that few respondents had a very high number of conditions.

Depressive symptoms

The NSHAP Depressive Symptoms Measures (NDSM) is based on the Iowa short-form of the Center for Epidemiological Studies—Depression (CES-D) scale (62). Participants were asked if they experienced 11 symptoms *rarely or none of the time*, *some of the time*, *occasionally*, and *most of the time* during the past week. These included items such as "I felt depressed," "everything I did was an effort," and "I felt lonely." Based on prior NSHAP studies (62), we combined the 2 most frequent response categories into 1, termed *much or most of the time*, to achieve full comparability of the NDSM to the well-validated CES-D short-form.

Table 1. Observed Social Network Indicators in National Social Life, Health, and Aging Project (NSHAP)

Network Characteristics	Interview Questions	Final Variable Coding
Number of core confidants	Looking back over the last 12 months, who are the people with whom you most often discussed things that were important to you?	Sum of number of confidants, recoded as: 1 = 0–2 confidants 2 = 3–4 confidants 3 = 5+ confidants
Number of family	Other than partner, how many family members or relatives do you have whom you feel close to? (0) *none*, (1) *one*, (2) *two or three*, (3) *four to nine*, (4) *ten to twenty*, (5) *more than twenty*	Sum of number of family ties recoded as: 1 = 0–3 ties 2 = 4–9 ties 3 = 10+ ties
Number of friends	About how many friends would you say that you have? (0) *none*, (1) *one*, (2) *two or three*, (3) *four to nine*, (4) *ten to twenty*, (5) *more than twenty*	Sum of number of friends recoded as: 1 = 0–3 ties 2 = 4–9 ties 3 = 10+ ties
Network diversity	Which of the following best describes [name]'s relationship to you? (1) *spouse*, (2) *ex-spouse*, (3) *romantic/sexual partner*, (4) *parent*, (5) *parent-in-law*, (6) *child*, (7) *stepchild*, (8) *brother or sister*, (9) *other relative of yours*, (10) *other in-law*, (11) *friend*, (12) *neighbor*, (13) *coworker or boss*, (14) *minister, priest, or other clergy*, (15) *psychiatrist, psychologist, counselor, or therapist*, (16) *caseworker/social worker*, (17) *housekeeper/home health care provider*, (18) *other*	Sum of number of different relationship types across all confidants: 1 = 1–2 different relationship types 2 = 3 different relationship types 3 = 4+ different relationship types
Frequency of contact	How often do you talk to this person? (1) *less than once a year*, (2) *once a year*, (3) *a couple times a year*, (4) *once a month*, (5) *once every two weeks*, (6) *once a week*, (7) *several times a week*, (8) *everyday*	Number of times the respondent talked to each confidant was recoded into interactions per year (eg, "once a month" = 12 times per year; "every day" = 365 times per year), averaged across all confidants, and categorized as: 1 = 0–173 times per year 2 = 174–248 times per year 3 = 249–365 times per year
Family support	How often can you open up to members of your family if you need to talk about your worries? How often can you rely on them for help if you have a problem? (1) *hardly ever*, (2) *some of the time*, (3) *often*	Coded as "1 = low" if responded "(1) *hardly ever*" to both questions; as "3 = high" if responded "(3) *often*" to both questions; and as "(2) = medium" otherwise.
Friend support	How often can you open up to your friends if you need to talk about your worries? How often can you rely on them for help if you have a problem? (1) *hardly ever*, (2) *some of the time*, (3) *often*	Coded as "1 = low" if responded "(1) *hardly ever*" to both questions; as "3 = high" if responded "(3) *often*" to both questions; and as "(2) = medium" otherwise.
Strain from family	How often do members of your family make too many demands on you? How often do they criticize you? (1) *hardly ever*, (2) *some of the time*, (3) *often*	Coded as "0 = Absent" if responded "(1) *hardly ever*" to both questions, and as "1 = Present" otherwise.
Strain from friends	How often do your friends make too many demands on you? How often do they criticize you? (1) *hardly ever*, (2) *some of the time*, (3) *often*	Coded as "0 = Absent" if responded "(1) *hardly ever*" to both questions, and as "1 = Present" otherwise.

The 2 positive items, "I was happy" and "I enjoyed life," were reverse-coded. Scores on each of the 11 items were summed to produce a total score ranging from 0 to 22, with higher scores indicating more depressive symptoms.

Birth cohort

To explore cohort differences in network type membership, participants were divided into 2 cohorts: (i) those born in 1930–1939 and therefore 66–75 years old at round 1 in

2005 (N = 1,080); (ii) those born in 1940–1950 and therefore 65–75 years old at round 3 in 2015 (N = 849).

Statistical Analysis

To identify social network types, we used LCA. LCA allows the measurement of a latent phenomenon, such as social network type, which cannot be directly observed or measured. The latent phenomenon is measured based on a set of observed indicators, in this case, the 9 observed social network characteristics. Based on participants' responses to the observed items, LCA groups participants with similar social network patterns together into classes, such that each class represents a distinct social network type. Latent classes are treated as mutually exclusive and exhaustive. Starting from a single-class model, we stepwise increased the number of classes until the model fit leveled off and we obtained conceptually distinct network types that were meaningful. Model fit was determined using information criteria, including the Akaike information criterion, Bayesian information criterion, adjusted Bayesian information criterion, and entropy, which is a measure of latent class separation (63). The final model with the optimal number of classes was selected on the basis of a combination of model fit, parsimony, and interpretability. To examine how membership in network types varied by sociodemographic characteristics, health characteristics, and birth cohort, we ran descriptive statistics examining the mean and standard deviation for continuous variables and the number and percent for categorical variables. Bivariate multinomial logistic regression was used to obtain p values to determine if the differences in network type membership by participant characteristics were statistically significant. Network types from the LCA were assigned based on the maximum posterior probability of membership. We also examined the multivariable association between sociodemographic and health characteristics and membership in network types using multinomial logistic regression. In the multinomial logistic regression models, participant characteristics were treated as independent variables and network type was treated as the nominal dependent outcome.

All statistical analyses accounted for stratification and clustering of the NSHAP sample design, unequal probabilities of selection, and nonresponse to calculate weighted, nationally representative population estimates and "robust" standard errors. Analyses were conducted in SAS 9.4.

Results

Latent Network Types

The Supplementary Table shows fit statistics for models with 2- to 6-class solutions. The likelihood ratio and information criteria suggest that the model fit improves as the number of classes increases. The Akaike information criterion, Bayesian information criterion, and adjusted Bayesian information criterion continue to decrease as more classes were added. However, beyond the 5-class solution, class sizes became too small (less than 10%) and the classes were more difficult to interpret meaningfully. Given that the difference in fit measures and entropy was minor between the 4- and 5-class solution, following Oberski's recommendation, we made our final model choice based on "ease of interpretation" (64). Theoretically, the results of the 5-class solution were more meaningful and allowed for a more nuanced interpretation of the network types, compared to the 4-class solution, and was therefore chosen as the preferred solution.

Table 2 provides an overview of the 5 latent social network types, their prevalence in the NSHAP sample, and the distribution of the observed network variables across classes. Network type labels were assigned to latent classes based on the overall and relative pattern and distribution of the item-response probabilities for each class. All network types are defined based on network size. Strain in broader family and friend relationships helped to distinguish 2 of the 5 types. Similarly, diversity in core confidant ties and frequency of contact helped to distinguish 2 additional types.

Type 1: large with strain (14%)

The first network type was characterized by an extensive number of core confidants and friends, and a moderate number of family ties. Approximately 80% of individuals in this type reported having 5 or more confidants and 60% reported having 10 or more friends. Approximately two-thirds of the respondents in this type reported having at least 4 different types of relationships among their confidants. Although more than half of the individuals reported high perceived support from family, they were also very likely to report experiencing strain in family ties. In fact, this was the only network type where all individuals reported the presence of strain in family ties. This was also the least prevalent network type in the sample.

Type 2: large without strain (23%)

Like individuals in the *large with strain* network type, individuals in this type reported a higher number of confidants and friends, and a moderate number of family ties. Approximately half of the individuals in this network type reported having at least 4 different types of relationships among their confidants. Similar to type 1, individuals in this type reported high support from family. However, unlike type 1, only 3% of individuals in this type reported experiencing any strain in family ties, and only 8% reported experiencing any strain in friend ties—the lowest among all the network types.

Type 3: small, diverse, low contact (26%)

The third type was characterized by an overall small network; although 59% of individuals in this type reported having 5 or more confidants, the majority also reported having a small family network (0–3 ties) and a small to medium friends' network (4–9 ties). Eighty percent of individuals in this type reported having at least 3 different types of relationships—the second-highest report of

Table 2. Weighted Five Latent Classes of the Social Network Types of Older Adults (unweighted *N* = 5,192)

Items		Latent Classes (Prevalence)				
		Large With Strain (14%)	Large Without Strain (23%)	Small, Diverse, Low Contact (26%)	Small, Restricted, High Contact (20%)	Medium Size and Support (17%)
		Probability of Endorsing Item				
Structural network characteristics	Number of confidants					
	0–2 confidants	0.01	0.03	0.00	0.84	0.25
	3–4 confidants	0.20	0.16	0.40	0.16	0.75
	5+ confidants	0.79	0.82	0.59	0.00	0.00
	Number of family					
	0–3 ties	0.17	0.17	0.62	0.59	0.36
	4–9 ties	0.52	0.52	0.34	0.29	0.43
	10+ ties	0.31	0.31	0.04	0.11	0.21
	Number of friends					
	0–3 ties	0.08	0.08	0.40	0.47	0.21
	4–9 ties	0.32	0.32	0.41	0.28	0.35
	10+ ties	0.60	0.59	0.19	0.25	0.44
	Network diversity					
	1–2 different ties	0.06	0.12	0.15	0.86	0.41
	3 different ties	0.34	0.40	0.43	0.10	0.56
	4+ different ties	0.60	0.49	0.42	0.04	0.03
	Frequency of contact					
	0–173 times a year	0.28	0.46	0.48	0.15	0.26
	174–248 times a year	0.43	0.36	0.35	0.22	0.35
	248–365 times a year	0.29	0.18	0.17	0.63	0.39
Functional network characteristics	Family support					
	Low	0.15	0.09	0.54	0.56	0.10
	Medium	0.28	0.30	0.30	0.26	0.35
	High	0.57	0.62	0.17	0.18	0.56
	Friends' support					
	Low	0.35	0.32	0.72	0.76	0.38
	Medium	0.30	0.30	0.18	0.15	0.36
	High	0.35	0.38	0.10	0.09	0.26
	Strain from family					
	Absent	0.00	0.97	0.44	0.54	0.70
	Present	1.00	0.03	0.56	0.46	0.30
	Strain from friends					
	Absent	0.63	0.92	0.75	0.76	0.84
	Present	0.37	0.08	0.25	0.24	0.16

network diversity in the sample. Despite having a large network of confidants, almost half of the individuals in this type reported low contact with their confidants. Overall, they reported low support from friends and family and low strain from friends. More than half of the respondents reported high strain from family. This was the most prevalent network type in our sample.

Type 4: small, restricted, high contact (20%)

Like the third type, the fourth type included individuals who had a small network of confidants, family, and friends. Contrary to the third type, this group had a relatively restricted network with 86% of individuals having no more than 2 different types of relationships in their confidant network. Despite the low diversity, individuals in this type had frequent contact with their ties, with more than two-thirds of the individuals reporting almost daily contact with their core confidants. Their perceived support from family and friends, and perceived strain from friends were comparable to those of individuals in the third type. Individuals in this type were slightly less likely to report strain from family compared to the third type.

Type 5: medium size and support (17%)

Individuals in the fifth type reported a medium-sized network of confidants (3–4 ties) and family (4–9 ties) and medium- to large-sized network of friends (4–10+ ties). More than half of the individuals in this type reported medium levels of network diversity (3 different relationship types). Although many individuals in this network type reported high support from family, they did not report high support from friends. Most reported experiencing no strain in family and friend ties.

Sociodemographic Correlates of Social Network Types

Table 3 shows the weighted descriptive statistics of the full sample and broken down by network type. *p* values from the bivariate multinomial logistic regression model predicting network type membership, with the *large without strain* network type as the reference category are also presented. We chose the *large without strain* network type as the reference type as it had a high prevalence and reflected the most well-endowed network type. Table 4 shows the odds ratios (ORs) and 95% confidence intervals from the multivariable multinomial logistic regression. The average age of the participants was 66.3 years (SD = 7.5), with those in the *small, restricted, high contact* type being the oldest (mean = 67.5; SD = 7.7). In the fully adjusted model, for a 1-year increase in age, the odds of being in type 1—*large with strain*—decreased by 2% (OR = 0.98, p = .007); whereas the odds of being in type 4—*small, restricted, high contact*—compared to the *large without strain* network type increased by 2% (OR = 1.02, p = .015). Over half of the sample was female (51.5%). The largest proportion of females was in type 2—*large, without strain* (24.9%)—and the smallest proportion of females was in type 4—*small, restricted, high contact* (14.8%). In contrast, the largest proportion of males was in type 3—*small, diverse, low contact* (26.6%)—and the smallest proportion of males was in type 1—*large with strain* (9.0%). Compared to men, women had higher odds of being in the *large with strain* network type (OR = 1.61, p < .0001) and lower odds of being in the *small, diverse, low contact* (OR = 0.68, p = .001) and the *small, restricted, high contact* (OR = 0.39, p < .0001) network types relative to the reference group. More than two-thirds of the sample was either married or living with a partner. The largest proportion of married or partnered individuals was in types 2—*large, without strain* (25.4%)—and 3—*small, diverse, low contact* (25.8%). Compared to not married individuals, married individuals or those living with a partner had significantly lower odds of being in type 4—*small, restricted, high contact* (OR = 0.53, p < .0001)—and type 5—*medium size and support* (OR = 0.66, p = .0001)—compared to the reference type. The majority of the sample was White (78.9%). The biggest proportion of Black and Other individuals was in types 3—*small, diverse, low contact* (27.3% and 28.3%, respectively)—and 4—*small, restricted, high contact* (23.8% and 29.4%, respectively); whereas White individuals were most likely to be classified into the *large without strain* network type. Compared to White individuals, Black and Other individuals had almost twice the odds of being in each of the other network types compared to the reference type, *large without strain*. They each had the highest odds of being in type 4—*small, restricted, high contact* (OR_{Black} = 2.04, p < .0001; OR_{Other} = 3.03, p < .0001). Two-thirds of the participants had at least vocational training/some college/Associate's degree (60.4%). The largest proportion of individuals with a high school or lower education was in the *small, restricted, high contact* network type (26.3%); and the largest proportion of individuals with a Bachelor's degree or higher was in type 2—*large without strain*. Compared to those with a high school or less education, those with at least a vocational/Associate's/some college or higher degree had lower odds of being in the *small, restricted, high contact* ($OR_{vocational}$ = 0.58; p < .0001; $OR_{Bachelor's}$ = 0.39; p < .0001) and *medium size and support* ($OR_{vocational}$ = 0.71; p = .001; $OR_{Bachelor's}$ = 0.51; p < .0001) network types compared to the reference group.

Health Correlates of Network Types

On average, participants had 1.6 chronic conditions (SD = 1.4; range = 0–8). In the fully adjusted model, we observed no difference in network type membership by the number of chronic conditions. On average, participants had a score of 4.9 on the NDSM for depressive symptoms (SD = 4.2; range = 0–22), with those in the *small, diverse, low contact* type reporting the highest scores at 5.6 (SD = 4.4). In the fully adjusted model, for a 1-unit increase in depressive symptoms score, the odds of being in the *large with strain* type (OR = 1.06, p < .0001), the *small, diverse, low contact* type (OR = 1.09, p < .0001), and the *small, restricted, high contact* type (OR = 1.06, p < .0001), compared to the *large without strain* network type, increased by 6% to 9%.

Differences in Network Type Membership by Birth Cohort

Comparison of the proportion of individuals (weighted data) assigned to each network type is suggestive of differences in network type membership between the earlier (1930–1939) and later (1940–1950) cohort (see Figure 1). The earlier cohort included greater proportions in network types 1 (*large with strain*), 4 (*small, restricted, high contact*), and 5 (*medium size and support*), whereas the later cohort included greater proportions in network types 2 (*large without strain*) and 3 (*small, diverse, low contact*). *p* values from the bivariate multinomial logistic regression model, with network type 2 (*large network without strain*)

Table 3. Weighted Sample Descriptive Statistics by Social Network Type (unweighted N = 5,192)*,†

			Type 1:			Type 2:		Type 3:			Type 4:			Type 5:		
	Full Sample		Large With Strain			Large Without Strain		Small, Diverse, Low Contact			Small, Restricted, High Contact			Medium Size and Support		
Participant Characteristics	*N*	%	*N*	%	*p* Value	*N*	%	*N*	%	*p* Value	*N*	%	*p* Value	*N*	%	*p* Value
Age (in years)‡	66.3	7.5	65.0	7.3	.005	66.2	7.6	65.4	7.2	.016	67.5	7.7	.002	67.2	7.6	.019
Gender																
Male	2 549	48.5	229	9.0		556	21.9	676	26.5		626	24.6		459	18.0	
Female	2 711	51.5	461	17.0	<.0001	674	24.9	620	22.9	.006	400	14.8	<.0001	552	20.4	.939
Marital status																
Married/ living with a partner	3 647	69.3	500	13.7	.285	925	25.4	940	25.8	.189	628	17.2	<.0001	654	17.9	<.0001
Not married	1 613	30.7	190	11.8		306	19.0	356	22.1		399	24.8		357	22.2	
Race/ethnicity																
White	4 144	78.9	553	13.4		1 077	26.0	986	23.8		731	17.6		794	19.2	
Black	566	10.8	79	14.0	<.0001	83	14.7	154	27.3	<.0001	134	23.8	<.0001	114	20.2	<.0001
Other	538	10.3	57	10.6	.014	70	13.0	152	28.3	<.0001	158	29.4	<.0001	102	18.9	.001
Education																
High school or less	2 088	39.7	233	11.2		403	19.3	435	20.9		548	26.3		466	22.3	
Vocational/Associate's/some college degree	1 777	33.8	248	14.0	.941	426	24.0	488	27.5	.570	290	16.3	<.0001	323	18.2	.001
Bachelor's+	1 395	26.5	209	15.0	.550	402	28.8	373	26.7	.178	189	13.5	<.0001	222	15.9	<.0001
Chronic conditions‡	1.6	1.4	1.6	1.4	.600	1.6	1.3	1.6	1.3	.704	1.7	1.3	.019	1.6	1.4	.792
Depressive symptoms‡	4.9	4.2	5.1	4.1	<.0001	4.2	4.0	5.6	4.4	<.0001	5.2	4.3	<.0001	4.3	4.0	.259

Notes: *Row percentages sum to a 100% across the 5 types. *N* for the full sample does not always equal the sum of *N*s across the 5 classes because of missing data on class membership for some individuals.

†*p* Values from bivariate multinomial logistic regression with *Type 2: Large without strain* as the reference group. Multinomial logistic regression modeled the odds of being in each of the care types compared to the reference type 2 for a 1-unit increase in age, a 1-unit increase in number of chronic conditions, a 1-unit increase in depressive symptoms, comparing females to males (reference), comparing married to unmarried (reference) individuals, and comparing Black and Other individuals to White (reference) individuals, and comparing those with vocational/Associate's/some college degree, and Bachelor's degrees to those with high school or less education (reference).

‡Means and standard deviations presented for the continuous variables.

Table 4. Multivariable Multinomial Regression Results Modeling the Odds of Membership in Each Network Type Relative to Type 2 for Sociodemographic and Health Covariates (unweighted *N* = 5,171)

	Type 1:		Type 2:	Type 3:		Type 4:		Type 5:	
	Large With Strain		Large Without Strain	Small, Diverse, Low Contact		Small, Restricted, High Contact		Medium Size and Support	
Participant Characteristics	OR	95% CI		OR	95% CI	OR	95% CI	OR	95% CI
Age (in years)	**0.98**	**0.96, 0.99**	[Reference group]	0.99	0.97, 1.00	**1.02**	**1.00, 1.03**	1.01	1.00, 1.03
Gender (ref = male)									
Female	**1.61**	**1.27, 2.04**		**0.68**	**0.54, 0.85**	**0.39**	**0.31, 0.48**	0.83	0.67, 1.04
Marital status (ref = not married)									
Married/living with a partner	1.04	0.79, 1.37		0.96	0.77, 1.19	**0.53**	**0.42, 0.67**	**0.66**	**0.53, 0.81**
Race/ethnicity (ref = White)									
Black	**1.76**	**1.29, 2.40**		**1.96**	**1.46, 2.62**	**2.04**	**1.51, 2.76**	**1.68**	**1.25, 2.27**
Other	**1.57**	**1.07, 2.29**		**2.32**	**1.70, 3.17**	**3.03**	**2.08, 4.41**	**1.85**	**1.26, 2.73**
Education (ref = high school or less)									
Some college	1.02	0.78, 1.31		1.12	0.90, 1.40	**0.58**	**0.45, 0.75**	**0.71**	**0.56, 0.90**
Bachelor's or more	1.05	0.74, 1.49		0.95	0.74, 1.22	**0.39**	**0.28, 0.53**	**0.51**	**0.39, 0.67**
Chronic conditions	1.00	0.91, 1.10		0.95	0.86, 1.05	0.96	0.87, 1.06	0.92	0.83, 1.01
Depressive symptoms	**1.06**	**1.03, 1.09**		**1.09**	**1.07, 1.12**	**1.06**	**1.03, 1.08**	1.00	0.98, 1.03

Notes: CI = confidence interval; OR = odds ratio.
Bold values denote statistical significance at $p < 0.05$.

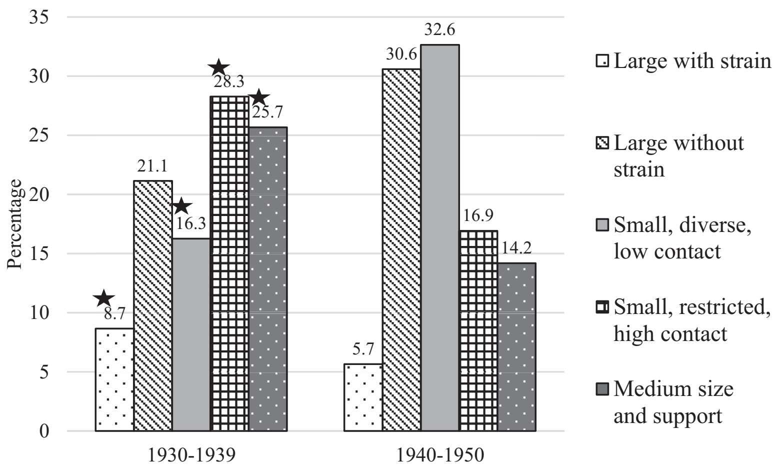

Figure 1. Weighted percentages reflecting membership in social network types by birth cohort (unweighted *N*: 1930–1939 = 1,080; 1940–1950 = 849). *Notes*: Percentages within each cohort sum to 100%. A star above the bars reflects a statistically significant difference in network type membership ($p < .05$) by birth cohort comparing each network type to the reference type 2, *large without strain.*

as the reference category, indicate that these differences are statistically significant.

Discussion and Implications

This study identified 5 distinct social network types: (i) *large with strain*, (ii) *large without strain*, (iii) *small, diverse, low contact*, (iv) *small, restricted, high contact*, and (v) *medium size and support* in a nationally representative sample of older adults, using 9 different structural and functional network characteristics. Findings highlight the complexity and heterogeneity in older adults' social networks, and identify sociodemographic and health correlates of membership in the latent network types, as well as differences in network type membership by birth cohort.

Unlike previous studies that have primarily focused on structural characteristics (21,24,27,28,31,35,41,42,51,56,65–67), the present study, which combined structural and functional network features, shows that the two types of features are not always correlated. Even among studies that have simultaneously examined the structure and function of the network, the network types have primarily been delineated based on network composition (eg, *friend-focused*, *family-focused* networks (9,25,26,53)) rather than a combination of structural and functional characteristics. The 5 network types identified in the present study correspond broadly to the network types found previously, with some novel findings. For example, like Ellwardt et al. we observed 2 large networks and 2 small networks (33). However, with the addition of strain from family and friends as indicators, we were able to develop a more nuanced typology where the 2 large network types differed in the presence of strain from family. This suggests that having a large network may not always confer benefits, especially if ties in the network engage in excessive criticism or are too demanding. Previously, Nguyen identified a *strained* network type that had high reports of negative interactions among family and church networks (23,55). Reports of experiencing strain in relationship with friends were generally low in our study. One possible explanation for this is that older adults are more likely than younger adults to withdraw from relationships that are particularly demanding, negative, or dissatisfying, as posited by the socioemotional selectivity theory (36). And it is easier to withdraw from friendships that are toxic than it is to withdraw from family ties that are dissatisfying. In the present study, network types reporting high support did not always report low strain or vice versa. For example, although 57% of respondents in the *large with strain* network type reported high support from family, 100% of them also reported experiencing strain in family ties. This indicates that the inclusion of measures of social strain along with social support in the development of network typologies allows for the identification of more nuanced network types with varying levels of support and strain.

Additionally, we observed that various structural characteristics are not always correlated with one another. For example, we observed 2 small networks—1 diverse and 1 restricted. This suggests that having a small network may not necessarily be a disadvantage, especially if the network is diverse, as higher diversity is associated with a reduced risk of mortality, cognitive decline, and physical decline (7). The *small*, *diverse, low contact* and *small*, *restricted, high contact* network types are partially consistent with the previous literature (21,25,26,28–30,68,69). Previous studies that focused on network composition, such as the proportion of ties that are kin versus nonkin, were not able to further distinguish the *diverse* and *restricted* network types based on size and frequency of contact, as we did. Although some have included measures of contact frequency, it did not help to distinguish between the network types with the exception of Barrett and Gunderson who also identified low versus high contact types (54).

Consistent with previous research on social networks and the socioemotional selectivity theory, older participants were more likely to be in the *small, restricted, high contact* network type and less likely to be in the *large with strain* type compared to the *large without strain* network type (4,9,36). The socioemotional selectivity theory suggests that as adults age, they become more selective in who they spend time with. This usually results in smaller networks, and networks consisting of ties with whom older adults experience less strain and greater emotional closeness (36). Compared to men, women in our sample were more likely to be in the *large with strain* network type and less likely to be in the 2 small network types relative to the reference network type; this corroborates previous evidence that women tend to have larger social networks than men (5,39). Compared to unmarried individuals, married individuals or those living with a partner were less likely to be in the *small, restricted, high contact* and the *medium size and support* network types relative to the reference group; this is also consistent with prior research that shows married individuals have larger and more diverse networks than unmarried individuals (41,42). Unlike some other network typology studies that included marital status as a network variable, we included it as a sociodemographic variable. This is because marital status is qualitatively different from other aspects of the network context and many other network characteristics such as network size, diversity, support, and strain are highly influenced by marital status. Furthermore, among subgroups of nonmarried individuals (never married, separated, divorced, widowed) there is substantive heterogeneity that would be obscured by including a binary marital status variable as a network characteristic. By not including marital status as a network variable, our network items were not dependent on whether the person has a spouse.

Compared to White individuals, Black and Other individuals were more likely to be in each of the network types compared to the reference type; they had the highest odds of being in the *small, restricted, high contact* network type. This finding partially supports the previous literature, which suggests that Black and Hispanic individuals are more likely to report smaller, kin-centered networks, with a high frequency of contact (5,9). Compared to those with a high school or less education, those with at least some college or a Bachelor's degree or more were least likely to be in the *small, restricted, high contact* network compared to the *large without strain* network type. This corroborates previous evidence that individuals with more education have larger, and more diverse networks, partly because it expands one's nonkin and community ties (70).

Besides differences in the sociodemographic composition of the network types, mental health emerged as an important correlate of network type membership in our study. Individuals who report higher depressive symptoms find their social interactions to be less rewarding (71); they are also more likely to withdraw from social relationships as a way of coping with their symptoms and therefore may report fewer ties, lower social support, or higher strain in relationships (72–74). Consistent with this view, individuals with higher depressive symptoms were more likely to be in type 1 which had higher reports of strain. They were also more likely to be in one of the smaller networks compared to the *large without strain* type. Contrary to our expectation, the number of chronic conditions was not associated with network types. This is in contrast to previous findings that have shown a relationship between various health conditions and network characteristics (75–77). This discrepancy from the previous literature is partly because null results tend to be underreported, with the exception of a few studies that found social network profiles of individuals to be indistinguishable in terms of physical well-being (51). It is also possible that the impact of chronic conditions on social networks may vary by condition; some conditions, like dementia, that affect daily functioning might have more of an impact on social networks than other conditions, like diabetes, that affect daily functioning less. Our current measure of the number of chronic conditions does not allow us to capture differences by type of condition.

In our exploratory analysis, birth cohort emerged as an important correlate of network type membership. Individuals in the later birth cohort (1940–1950) were significantly more likely to be in the *small, diverse, low contact* network type compared to those in the earlier cohort (1930–1939). Individuals in this network type were likely to report 0–3 family ties but 4–9 friendship ties, and a majority of the individuals in this network type reported having at least 3 different types of relationships—the second-highest report of diversity in the sample. Although individuals in this type reported a greater number of friends, their reports of support from both friends and family were low. This suggests that across subsequent birth cohorts, although friendship networks may be larger, they are not necessarily more supportive than family networks. Although we did not have a specific hypothesis for this exploratory aim, our findings partially corroborate those of the other two studies to our knowledge that have explored cohort differences in network typology. In a Dutch cohort, Suanet et al. found that later birth cohorts were more likely to have diverse networks with more friends and fewer family members (10). In contrast to Suanet et al., our measure of network type went beyond network composition to include support and strain in networks; we found that the *large with strain* network type was less common in the later cohort.

Some limitations of the present study should be acknowledged. Although comprehensive data on various measures are available in NSHAP, the social network data are collected through self-report, and therefore may be subject to unreliable recall and social desirability bias (78). Because NSHAP excluded respondents with a history of dementia, unreliable recall may be less of an issue. And there is some evidence to suggest that network data based on recall are better for understanding participants' perceptions of support in social relationships (78). NSHAP data as yet does not afford the opportunity to do a formal Age–Period–Cohort analysis and so our findings are limited to an exploratory analysis of differences in network types between two birth cohorts. We did ensure that the age range of the two birth cohorts was close to identical in order to control for the effect of age. However, our approach does not exclude the possibility of a period effect on network type membership and more research is needed to disentangle age, period, and cohort effects in more detail. In addition, we relied on cross-sectional data from NSHAP and did not address the degree to which network types for individual older adults may change as they become older. Future research should consider how changes in individual and situational contexts lead to transitions in network types as adults age. Lastly, the present study focused on the number of chronic conditions as an indicator of physical health as it is a manifestation of multiple universal health outcomes including functional capacity, symptom burden, self-rated health, quality of life, and survival. Evaluation of specific health outcomes, such as functional capacity, or specific conditions, such as heart failure, as predictors of network type membership was beyond the scope of the present study but could be the focus of future research.

Despite these limitations, findings from the present study elucidate the varied interpersonal environments in which older adults are embedded and can be used to identify the kinds of resources available to them, such as family and friend caregivers, that they may call upon during times of serious illness, hospitalization, and other difficulties in daily life. This network approach can prove useful in identifying older adults who are at an increased risk of becoming socially isolated, such as those in smaller and more restricted networks. Individuals at risk of social isolation or with insufficient support can be targeted for opportunities for social engagement through participation in educational, social, and physical activity programs, thereby improving the emotional well-being and quality of life of older adults.

Supplementary Material

Supplementary data are available at *Innovation in Aging* online.

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Conflict of Interest

None declared.

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