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Social Network Types and Self-Rated Health Among Diverse Older Adults: Stability, Transitions, and Implications for Health Equity

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Abstract

Background and objectives: This study explores how social networks among older adults evolve over time and their impact on self-rated health (SRH), emphasizing differences across ethnoracial and linguistic groups. Though the link between social networks and well-being is well-known, how these networks change and affect health remains less understood.

Research Design and Methods: The study examined changes in social network types across 3 rounds of the National Social Life, Health, and Aging Project. The initial sample included 3 005 individuals, which decreased to 1 592 by the final follow-up. We analyzed data from participants in every round, totaling 6 858 observations, using Random-Intercept Latent Transition Analysis. Multinomial logistic regressions were conducted to predict network membership and transitions and to assess correlations with SRH.

Results: We identified 3 distinct social network types: "Enriched," "Focused," and "Restricted." "Enriched" networks feature broad connections, high marriage rates, active engagement, and low loneliness. "Focused" networks involve small, close-knit groups with frequent interactions, moderate marriage rates, and low loneliness. "Restricted" networks are family-oriented, with low marriage rates and the highest loneliness levels. Over time, "Restricted" networks became more prevalent, whereas "Focus" networks showed the most mobility. Network type membership varied significantly by ethnoracial identity and gender, with Black, Hispanic, and female respondents less likely to belong to "Enriched" networks. Membership in "Enriched" networks was linked to better SRH scores.

Discussion and Implications: The growth of "Restricted" networks over time raises concerns about older adults becoming confined to limited social environments. However, there is a silver lining: within the "Focused" group, more individuals transition to "Enriched" networks than to "Restricted" ones, indicating that older adults can expand their social connections as they age. Understanding the factors driving this shift can guide interventions to promote network expansion for vulnerable groups, enhancing social well-being, and mitigating the risks associated with restricted networks.

Keywords: Aging and life course, Health disparities, Health trajectories

Translational Significance: Social networks significantly impact the health and well-being of older adults, yet their evolution in diverse aging populations remains less understood. This study identified 3 network types: "Enriched," "Focused," and "Restricted," with "Restricted" networks becoming more common over time, revealing vulnerabilities that worsen with age and reflect persistent inequities. However, the mobility within "Focused" networks offers hope, as more individuals transitioned to "Enriched" than "Restricted" networks, suggesting opportunities to expand connections. These findings highlight the need for targeted interventions, particularly for women and minority groups, to strengthen social networks and improve health and quality of life in later years.

Background and Objectives

We are embedded in complex interpersonal connections partly shaped by ourselves (1,2). This network is not just a backdrop but an active framework shaping our behaviors, beliefs, and well-being. Studying these connections helps us understand how individual agency and social structure influence daily life (1,2). Rich networks with frequent interactions provide efficient support by enabling members to quickly identify problems and mobilize emotional and instrumental aid (3,4). For example, Freidenberg and Hammer (1998) found that Hispanic older adults with strong social networks were less likely to have unmet medical needs compared with those with weaker networks (5).

However, strong social networks can also infringe on privacy and autonomy. Conversely, "weak" ties—connections linking individuals to different groups via a shared member—grant access to unique information and resources, enhancing independence and control (6,7). Given the mixed effects of social ties, it is essential to explore how different

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network types and their characteristics affect health outcomes throughout life stages.

Network Types and Their Health Implications

The complexity of social ties suggests that networks should be viewed holistically, encompassing their structure, function, and quality (8,9). Specifically, these terms are characterized as follows: (1) structure refers to the patterns of relationships and connections among contacts; (2) function denotes the extent to which self-identified needs are perceived to be met; and (3) quality represents satisfaction with those relationships. Research shows that the size and diversity (ie, *structure*) of these networks matter for older adults' health outcomes (7). Broad networks enable 'bridging' ties that provide access to different social sectors, offering *functional* advantages like instrumental and socioemotional help (10,11). Traditionally, network *quality* has been defined as "satisfaction" with one's family and friends (9), but a more meaningful measure of *quality* may be the absence of personal loneliness, arising from a gap between expected and actual social connection (12,13).

Loneliness, though influenced by both functional and structural factors, is distinct. Although structural changes like age-related declines in health and social relationships can increase loneliness, many older adults adapt to maintain social involvement despite challenges (13,14). They frequently prune their networks to focus on meaningful relationships (15), suggesting that loneliness within a network may provide deeper insights than mere satisfaction. Moreover, loneliness negatively affects health and longevity (13,16). These 3 dimensions—structure, function, and quality—interact in complex ways, with combined effects that promote or hinder healthy aging.

Understanding the interplay between the structure, function, and quality of social networks highlights the need to examine specific "types" of networks. Different "types" of networks have been found to affect health outcomes distinctly (17–19). Restrictive networks, often limited to close family, are associated with more health problems than larger and more diverse networks. Studies demonstrate that varied and extensive connections enhance cognitive health by protecting against social isolation linked to cognitive decline (20,21).

Robust networks not only slow cognitive decline but also improve overall mental health and chronic conditions like hypertension (18,22). Individuals with larger networks who discuss health issues within their network have lower risks of undiagnosed and uncontrolled hypertension (22). Those in networks with greater social capital are less lonely, less anxious, and happier than those in less enriched networks (18). Older adults in resource-rich networks are more likely to adopt healthy behaviors, such as physical activity and moderate alcohol consumption (19). Conversely, limited social connections are linked to higher health risks and premature death (12,16).

Social networks evolve significantly with age, becoming more family-centric. The convoy model and socioemotional selectivity theory suggest that over time older adults prioritize emotionally significant relationships, focusing on familiar partners and family members (8,15,23). Research shows aging networks become more family-oriented and meaningful, especially in later life, which may be the longest life phase (24,25). However, racial and ethnic disparities complicate this process, as social disadvantages can shape networks, influencing health and life trajectories (26).

By examining how racial and ethnic disparities intersect with network evolution, this study aims to highlight broader implications for health, well-being, and social support systems in diverse aging populations. Understanding these nuances may help address challenges faced by older adults from different backgrounds.

Ethnoracial Differences in Social Networks

Current literature on aging and social networks often overlooks the impact of ethnoracial identity and English proficiency, despite their crucial role in shaping social networks. Experiences of racial discrimination and varying language skills significantly influence the formation, maintenance, and quality of social networks among older adults of different backgrounds. Research indicates that older Black and White adults' social networks differ significantly due to social disadvantages like eviction, unemployment, poverty, and incarceration, which disrupt social environments and reduce network size and quality (27–29). These hardships disrupt social environments, leading to reduced network size and quality. Economic uncertainties and job insecurities further erode social interactions, making it difficult to maintain relationships. Racial discrimination can lead to the selective formation of networks that provide emotional and instrumental support, thereby shaping the structure and function of these networks (27). Prolonged crises can also cause network shrinkage, resulting in smaller, more kin-centered networks among Black older adults compared to their White counterparts. Even those with higher socioeconomic status may face subtle forms of discrimination affecting service use and access to health resources (30,31).

English language proficiency also influences social networks. Although many Hispanic adults are bilingual, a notable portion of those over 65 are monolingual Spanish speakers (32). Language barriers limit community interactions and service access, constraining network diversity and size. These challenges lead to reliance on monolingual networks of family and community members, affecting the overall network structure and support mechanisms (33,34). Literature highlights the negative consequences of language mismatches within the healthcare system, impeding access and reducing compliance with medical recommendations (34–36). Although both Black and Hispanic older adults may have smaller, insular networks due to social disadvantages, their experiences and network evolution differ.

Hispanic older adults often have smaller, denser networks and face economic challenges as well as significant segregation compared to White older adults (37,38). However, cultural strengths and familial ties provide essential support despite obstacles. Although those with families abroad may have smaller networks, marital quality serves as an important social support in later life; one study linked marital satisfaction to lower depressive symptoms among older Hispanic immigrants (39). Additionally, they are more likely to live in multigenerational households, providing additional support (40).

In contrast, Black older adults have faced distinct social disadvantages. Born between 1928 and 1945—the "Silent Generation" (41)—they were characterized by traditional values but faced restricted opportunities, especially for women (42–44). Although many Silent Generation women built their work and family lives before the feminist and civil rights movements could expand their options, Black men and women faced institutionalized racism that severely hindered their chances for social and economic advancement (43,45). Many lived in the South before the end of Jim Crow laws that enforced racial discrimination in Southern states (45). Evidence suggests that participation in the Great Migration—the movement from the rural South to urban areas in the North, Midwest, and West—though motivated by hopes for improved prospects, was associated with increased mortality among those born in the early twentieth-century South (44). Widespread racial discrimination before, during, and after the Great Migration led to racially homogeneous networks as African Americans sought supportive communities amid systemic barriers and hostility, further influencing the structure and resilience of their social networks (46,47).

Understanding how social network types vary among diverse groups and evolve over time is crucial (48). Our research explores the varied nature of social networks within different social contexts. Our research explores this by employing a nominal latent variable to examine how network types correlate with self-rated health (SRH) across racial and ethnic groups over time. We address three questions: What types of social networks exist among older adults? How does network membership change over time across groups? Does network membership affect SRH?

We focus on SRH as our key outcome due to its effectiveness in evaluating overall health and predicting mortality, functional impairment, and cognitive impairment among older adults (49,50). SRH's strong association with mortality across populations suggests that it is a comprehensive measure of health status, capturing aspects of general health beyond clinical diagnoses (51–53). Kananen et al. (2021) validated SRH by correlating it with multiple biomarkers, demonstrating that SRH has a solid biological basis and serves as a valid, though non-specific, indicator of well-being (53).

Our study is distinguished by its analytical method. Previous research used latent class analyses (LCA) (20) or cluster analyses (9,18,54) to identify network types, assigning membership based on the highest predicted probability (55). Although effective for identifying network types, these methods fail to track changes over time as they don't model the probability of transitioning between classes. We employ Random-Intercept Latent Transition Analysis (RI-LTA), which allows us to fit groupings at separate data rounds and treat transitions as another latent variable (56).

This approach enables us to predict network membership and transitions using covariates, enhancing our understanding of how ethnoracial identity influences network evolution over time. By adopting RI-LTA, our study offers a dynamic perspective on social network changes and their effects on health outcomes, contributing to a better understanding of how social structures influence the well-being of older adults across diverse populations.

Research Design and Methods

Data

We used data from 3 rounds of the National Social Life Health and Aging Project (NSHAP) collected during 2005–2006, 2010–2011, and 20152016 (57). NSHAP is a longitudinal study of a probability sample of older U.S. adults, initially targeting a representative group born between 1920 and 1947 with an oversampling of African Americans and Hispanic adults, including the oldest old. The first round (2005–2006) achieved a sample size of 3 005 and a 75.5% weighted response rate (58). The second round (2010–2011) reinterviewed initial participants and expanded to include their cohabiting spouses or partners, increasing the sample to 3 377 with a 74% response rate (59). The third round (2015–2016) continued with previous participants and added a new cohort of Baby Boomers born between 1948 and 1965, raising the sample size to 4,777 with a 76% response rate (60). Further recruitment and sample details are documented elsewhere (61). All data collection protocols (Protocol Number: 14.06.01) were approved by the National Opinion Research Center at the University of Chicago Institutional Review Board (IRB00000967) under Federalwide Assurance #FWA00000142, adhering to U.S. Department of Health and Human Services regulations. Participants provided written informed consent. NSHAP data are available in the National Archive of Computerized Data on Aging at the Inter-University Consortium for Political and Social Research, accessible at https://www.icpsr.umich.edu/web/NACDA/series/706.

Analytic Sample

For this study, we used the initial sample of 3 005 participants from Round 1 of the NSHAP survey, following those who continued to participate in subsequent rounds: 2 261 in Round 2 and 1 592 in Round 3. We analyzed data from each participant in every round, totaling 6 858 observations. All 3 rounds involved the same cohort, with individuals measured longitudinally at each time point. As such, transitions between rounds reflect within-cohort changes rather than cohort effects. Attrition between rounds was calculated by dividing the number of participants in the current round by the number in the previous round, providing insight into participant retention or dropout. Specifically, the attrition rate from Round 1 to Round 2 was approximately 24.76%, whereas the attrition rate from Round 2 to Round 3 was about 29.59%.

Ethnoracial identity, gender, and age were assessed at baseline. We employ the term "ethnoracial" to denote identities that blend racial and ethnocultural traits, recognizing these as socially constructed (62). Although "Hispanic" is not classified as a race, it is often treated as one (62). Our study did not distinguish between "White Hispanic" and "Black Hispanic" due to data limitations. Instead of specifying cultural heritage, we used language preference as a proxy to examine Hispanic diversity, acknowledging its significant role in shaping life experiences and health outcomes. Individuals in the "All Else" grouping identified with an ethnoracial category other than Black, Hispanic, or White. We retained the "All Else" group to avoid an unnecessary reduction in sample size, which could compromise the statistical power and generalizability of our findings. However, we refrain from drawing substantive conclusions about this group because its heterogeneous nature and small number make it difficult to identify any specific patterns or consistent characteristics.

Measures

Since its inception in 2005, NSHAP has been collecting detailed information about participants' social networks and any changes since the last interview. A key feature of NSHAP is the "important matters" name generator, which enables researchers to examine the network's structure, function, and quality with high precision (63).

Name generator

This tool asks respondents to identify up to 5 individuals with whom they frequently discussed significant matters over the past year. After listing these confidants, respondents provide details about each one, including their relationship to the confidant, the frequency of communication with them, and how often each confidant communicates with the others. NSHAP's name generator is notably rigorous compared to other datasets. The first round (2005–2006) set a high benchmark with no anomalous interviewers and low within-interviewer correlations, thus establishing it as the "gold standard" in survey-based network research (64).

The data derived from the name generator were analyzed to categorize response patterns into typologies. This analysis involved 3 distinct measurement types: indicators that describe the network's structure, functionality, social engagement, and quality were first examined in our latent class analyses. The second type comprised baseline covariates, and the third focused on SRH as the study's outcome variable.

Network Indicators

Structure

We examined 8 network structure variables, including marital status, household size (living alone, with one other person, or with 2 or more people), and the number of children. We also assessed *network size* by the number of individuals with whom respondents discuss "important matters." Additional structural features derived from this network included the average number of days per year spent interacting with confidants (*interaction frequency*), the *proportion of family* members among confidants, *network range* (calculated by the number of different relationship types divided by the total network size), and *network density* (measured by the number of actual ties relative to the possible links among confidants).

Although some of these variables may be correlated, they remain conceptually distinct. For example, *network size* may include a spouse but reflects the broader confidant network, which the spouse may or may not be part of. Household size is often correlated with marital status, as most married respondents live with their spouse. However, including marital status helps identify latent classes that are independent of whether the respondent has a coresident romantic or sexual partner.

Social engagement

We assessed the frequency of respondents' participation in activities outside their personal networks using 3 variables: attendance at religious services, volunteer work, and local meetings. Participation was categorized as either "at least once a week or more" or less frequently (0 = less often than once a week; 1 = once a week or more).

Function

We examined social network function by analyzing the support and strain experienced from friends, family, and spouses. Social network function is commonly defined as the provision of emotional, instrumental, and informational support, alongside the presence of negative interactions such as conflict or criticism (8,11). In this study, we define function as the extent to which a network is perceived as providing emotional support, balanced against the tension or strain experienced within those relationships (13). Support was measured by how often respondents felt they could confide in or rely on these groups, using 6 items for married respondents and 4 for unmarried respondents (Cronbach's $\alpha = 0.64$). Strain was measured by how often these groups were perceived as overly demanding or critical, with the same number of items (Cronbach's $\alpha = 0.60$). Both metrics were normalized across survey rounds and scored on a scale of 1–3, where higher scores indicate greater levels of support or strain.

Quality

Network quality was measured by assessing the absence of personal loneliness, defined as the gap between one's expectations for social connection and their actual experience (12,13). We used the 3-item UCLA loneliness scale, which asks respondents how often they feel left out, lack companionship, or feel isolated (Cronbach's $\alpha = 0.80$). Scores were standardized across rounds and ranged from 1 to 3, with higher scores indicating greater loneliness.

Covariates

Demographic covariates included respondents' self-reported gender, age at baseline, education level, and race/ethnicity. Race/ethnicity was divided into 5 categories: White, Black, Hispanic English-speaking, Hispanic Spanish-speaking, and All Else. The survey language served as an indicator of language preference.

SRH

We used SRH as our outcome variable. SRH has been extensively used as a reliable and valid health status measure in epidemiological and public health research. For SRH, respondents rated their overall physical health on a 5-point scale, with values ranging from 1 (poor) to 5 (excellent).

Analytic Strategy

To answer our 3 research questions, we identified network types, explored how network memberships evolved over time, and examined the relationship between various social network types and older adults' SRH.

Identifying network types

We used Random-Intercept Latent Transition Analysis (RI-LTA) to analyze the latent dynamics of social networks. This method extends LCA by grouping respondents based on the most likely network type derived from their responses and tracking these groups over different data collection times (56). The value of LTA is in its ability to track membership changes over time and link these changes to specific predictors. With this approach, we can assess how network type influences specific outcomes, such as SRH, while controlling for other factors. The "RI" component represents a random intercept, a continuous latent variable that captures stable aspects of social networks, providing a baseline for measuring changes over time. This approach allows us to model groupings at different rounds of data collection (R1-3) and consider transitions as another latent variable, thus predicting network-type membership and transitions based on covariates. Figure 1 illustrates the RI-LTA model details.

To ensure model identifiability and simplicity, we kept consistent network-type features and random intercept loadings

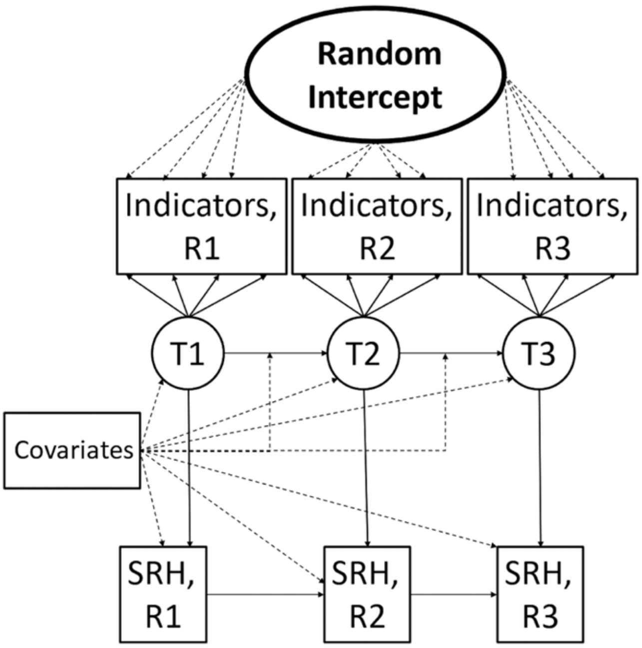

Figure 1. Diagram of random intercept latent transition model. R = data round; T = network type; SRH = self-rated health. Diagram omits error terms, for parsimony.

across all 3 data rounds. This was justified because the same respondents were measured at all time points, with minimal loss to follow-up, so continuity in the cohort supported a consistent factor structure over time. We constrained the factor structure for both analytic and computational reasons, as models struggled to converge without this constraint. Without strong theoretical guidance for a varying factor structure, imposing consistency across rounds was reasonable and necessary. Analyses were conducted using MPlus version 8.8.

Due to the absence of log-likelihood tests for survey designs in MPlus version 8.8, we relied on the Bayesian Information Criterion (BIC) to determine the optimal number of network types, as recommended in the literature (65). A lower BIC indicates a better model fit, typically identified when the BIC reaches a minimum before increasing with unnecessary classes (66). If the BIC decreases continuously, a plateau or slower rate of decline suggests the ideal number of network types (55). In our case, the BIC diminished progressively, but the rate of decline lessened after identifying 3 network types. Therefore, we determined that a 3-type model was most appropriate for our analyses.

Exploring the evolution of network memberships

To address our second research question, we conducted a 3-part analysis using Full Information Maximum Likelihood. This casewise likelihood method allowed us to retain all available data across rounds without imputing missing values. Specifically, we included 2 261 observations for transitions between Round 1 and Round 2 and 1 592 observations for transitions between Round 2 and Round 3. All non-missing data from each round were incorporated into the analysis.

First, we examined the transition probabilities between different network types from Round 1 to Round 2 and from Round 2 to Round 3 to understand the temporal changes in network memberships. We focused on how likely individuals were to move between network types throughout the study. Next, we used multinomial logistic regression to analyze how network membership varied across different ethnoracial and linguistic groups across all 3 rounds of data collection. Finally, we evaluated various covariates to determine their impact on the likelihood of transitioning between network types, identifying key factors that influence changes over time.

Network types and SRH

Lastly, we conducted an Ordinary Least Squares (OLS) regression analysis to predict SRH based on network type membership across 3 rounds, adjusting for NSHAP survey design elements such as weights, clusters, and strata, and accounting for attrition using inverse probability weighting (58). These weights depend on the accuracy of the selection model, so we included a range of demographic predictors and interviewer ratings regarding the difficulty of obtaining interviews. Although attrition may still introduce some bias, good-faith efforts have been made to minimize its effects.

Results

This study addressed 3 key questions: What types of social networks exist among older adults? How does network membership change over time across groups? Does network membership affect SRH? To answer these questions, we identified network types, explored factors influencing transitions, and assessed the impact of network-type membership on older adults' SRH.

Table 1 shows data across 3 rounds, indicating changes in participant demographics over time. Despite a decrease in total participants from 3 005 in Round 1 to 1 592 in Round 3, missing data remained minimal (0.44%–0.47%), and the ethnoracial composition stayed relatively stable, with a slight increase in the proportion of White adults by Round 3. Gender distribution was consistent, with a slight increase in female participants in the final round, reflecting the aging of the sample. SRH scores remained stable across all rounds, averaging around 3.20, indicating consistent perceived health among participants.

Table 2 summarizes demographic characteristics and self-reported measures across ethnoracial groups at Round 1, highlighting variations in gender, marital status, education, and self-rated health (SRH). Most groups had more females, except "Hispanic Spanish Speaking" and "All Else," where males constituted 51.79% and 60%, respectively. White participants were nearly gender-balanced, whereas Black and Hispanic English-speaking participants were predominantly female.

Marital status varied: Black participants had the lowest marriage rate at 41.8%, significantly lower than other groups ranging from 57.14% to 64.88%. White and Hispanic Spanish-speaking participants had the highest marriage rates, at 64.08% and 64.88%, respectively.

Education levels and SRH also differed. White and "All Else" participants had the highest education levels, averaging 13.46 and 13.83 years. Black and Hispanic English-speaking participants had lower averages of 11.49 and 11.09 years, whereas Hispanic Spanish-speaking participants had the lowest at 5.28 years. For SRH, White participants reported the highest average at 3.33, followed by the "All Else" group at 3.24 and the Hispanic English-speaking group at 3.21. Black and Hispanic Spanish-speaking participants reported lower SRH averages of 2.86 and 2.60.

We conducted a descriptive analysis of social network variables across groups in Round 1 (Table 3). Marital status and household composition showed clear differences: 64% of White participants were married compared to 42% of Black participants. Hispanic participants had marriage rates of 59% (English-speaking) and 65% (Spanish-speaking). Living alone was more common among Black participants (35%) than Hispanic Spanish-speaking participants (12%).

Family size varied, with Black (64%) and Hispanic Spanish-speaking (73%) participants more likely to have more than 3 children compared to Whites (51%). Network family proportions were similar across groups, though Hispanic English-speaking participants reported slightly higher figures (0.51). Hispanic Spanish-speaking participants displayed the highest network density, indicating closer social connections.

Network size and interaction frequency differed: White participants had the largest networks (average 3.68), whereas Hispanic Spanish-speaking participants had the smallest (2.75). However, Hispanic Spanish-speaking participants had the highest interaction frequency (270.47), suggesting more frequent engagement within their networks compared with Whites (196.87).

Social engagement also varied. Black participants most frequently attended religious services (56%), whereas the "All Else" group had the highest volunteering rate (29%). Volunteering among Hispanics was notably lower (8% English-speaking, 9% Spanish-speaking). Local meeting

Table 1. Demographic Characteristics and Self-Rated Health Across Rounds 1–3

Variables		Range	Round 1 (N = 3, 005)	Round 2 (N = 2 261)	Round 3 (N = 1 592)
Ethnoracial groups, n (%)					
	White		2 110 (70.54)	1 593 (70.77)	1 123 (70.85)
	Black		500 (16.72)	369 (16.39)	250 (15.77)
	Hispanic, English		143 (4.78)	111 (4.93)	77 (4.86)
	Hispanic, Spanish		168 (5.62)	127 (5.64)	101 (6.37)
	All Else		70 (2.34)	51 (2.27)	34 (2.15)
Gender, n (%)					
	Male		1 454 (48.39)	1 083 (47.90)	739 (46.42)
	Female		1,551 (51.61)	1,178 (52.10)	853 (53.58)
Marital status, n (%)					
	Married		1 801 (59.93)	1,290 (57.05)	888 (55.78)
	Other		1 204 (40.07)	971 (42.95)	704 (44.22)
Age (years), average (SD)		57-95	69.30 (7.85)	73.44 (7.51)	76.88 (6.79)
Education (years), average (SD)		0–32	12.59 (4.06)	12.92 (3.97)	13.09 (4.07)
Self-rated health, average (SD)		1–5[a]	3.20 (1.11)	3.20 (1.06)	3.23 (1.03)

[a]Indicates that higher value represents better outcomes.

Table 2. Demographic Characteristics by Ethnoracial and Linguistic Group (Round 1)

Variables		White (n = 2,110)	Black (n = 500)	Hispanic, English (n = 143)	Hispanic, Spanish (n = 168)	All Else (n = 70)
Gender, n (%)						
	Male	1 031 (48.86)	222 (44.40)	67 (46.85)	87 (51.79)	42 (60.00)
	Female	1 079 (51.14)	278 (55.60)	76 (53.15)	81 (48.21)	28 (40.00)
Marital status, n (%)						
	Married	1,352 (64.08)	209 (41.80)	84 (58.74)	109 (64.88)	40 (57.14)
	Other	758 (35.92)	291 (58.20)	59 (41.26)	59 (35.12)	30 (42.86)
Age in years, average (SD)		69.66 (8.02)	68.89 (7.31)	67.52 (7.59)	68.23 (7.35)	67.80 (7.40)
Education in years, average (SD)		13.46 (3.28)	11.49 (4.19)	11.09 (4.31)	5.28 (3.85)	13.83 (4.66)
Self-rated health (in 1–5[a]), average (SD)		3.33 (1.10)	2.86 (1.08)	3.21 (1.10)	2.60 (1.03)	3.24 (1.12)

[a]Indicates that higher value represents better outcomes.

Table 3. Means for Social Network Variables by Ethnoracial/Language Grouping (Round 1)

Variables	Range	White (n = 2,110)	Black (n = 500)	Hispanic, English (n = 143)	Hispanic, Spanish (n = 168)	All Else (n = 70)
Structure						
Married	0 or 1	0.64	0.42	0.59	0.65	0.57
Household size	1–3					
Alone	(1)	0.28	0.35	0.23	0.12	0.23
One other	(2)	0.58	0.38	0.47	0.50	0.49
2 or more	(3)	0.14	0.27	0.30	0.38	0.28
Children	1–4					
0	(1)	0.08	0.08	0.04	0.04	0.09
1	(2)	0.12	0.12	0.06	0.08	0.09
2	(3)	0.29	0.16	0.26	0.14	0.16
≥3	(4)	0.51	0.64	0.63	0.73	0.66
Network size	1–6 (*SD*)	3.68 (1.47)	3.31 (1.56)	3.42 (1.43)	2.75 (1.39)	3.37 (1.57)
Interaction frequency	0–365 (*SD*)	196.87 (82.13)	233.21 (90.21)	229.70 (88.89)	270.47 (81.14)	221.40 (90.13)
Proportion family	0–1 (*SD*)	0.42 (0.31)	0.49 (0.34)	0.51 (0.32)	0.44 (0.35)	0.47 (0.35)
Network range	0 –1 (*SD*)	0.66 (0.24)	0.66 (0.25)	0.64 (0.23)	0.74 (0.26)	0.67 (0.24)
Network density	0 –1 (*SD*)	0.71 (0.28)	0.75 (0.30)	0.80 (0.28)	0.89 (0.24)	0.78 (0.26)
Social Engagement						
Attends Religious Services	0 or 1	0.43	0.56	0.49	0.47	0.49
Volunteers	0 or 1	0.21	0.21	0.08	0.09	0.29
Attends local meetings	0 or 1	0.26	0.28	0.14	0.20	0.19
Function						
Support[a]	1–3 (*SD*)	2.44 (0.42)	2.39 (0.48)	2.33 (0.43)	2.40 (0.42)	2.43 (0.46)
Strain[a]	1–3 (*SD*)	1.29 (0.31)	1.41 (0.41)	1.41 (0.40)	1.29 (0.34)	1.40 (0.34)
Quality						
Loneliness[a]	1– 3 (*SD*)	1.32 (0.45)	1.49 (0.54)	1.37 (0.42)	1.40 (0.52)	1.45 (0.51)

[a]Higher value represents higher levels.

attendance was highest among Black participants (28%) and lowest among Hispanic English-speaking participants (14%).

Loneliness scores also varied, with White participants reporting the lowest average loneliness score (1.32) and Black participants the highest (1.49). Hispanic groups reported moderate scores of 1.37 (English-speaking) and 1.40 (Spanish-speaking).

What Social Network Types Exist?

We used RI-LTA to categorize respondents into social network types based on their data. This method fits groupings across data collection rounds (R1-3) and treats transitions as a latent variable, establishing a stable baseline for observing changes over time. Consequently, we can predict network-type membership and transitions based on covariates.

We conducted goodness-of-fit measures to determine the optimal number of classes. Supplementary Table 1 shows that BIC decreased with each additional class, with the largest decline between 2 and 3 classes. Entropy followed a similar pattern when LCAs were run separately for each round (see Supplementary Table 2).

With LTAs, entropy decreased at the 3-class solution, increased at 4 classes, and then declined again. Because higher entropy indicates greater class separation, this might suggest a 4-class solution. However, when latent class models were fit separately for each round, entropy peaked at three classes, making the entropy evidence ambiguous.

Supplementary Table 3 shows that for LTA and RI-LTA (Round 2), classes with fewer than 300 members appeared after the 3-class solution. Although the 300 threshold is arbitrary, the most pronounced drop-off occurred here, with only marginally smaller classes beyond 3 classes up to 7. Therefore, we selected the 3-class solution as the most parsimonious fit.

Table 4 presents the characteristics of the 3 latent network types: "Enriched" (large, diverse networks), "Restricted" (small, constrained networks), and "Focused" (intermediate category).

Table 4. Social Network Characteristics Across Different Network Types

Variables	Range	Network types		
		Focused	Enriched	Restricted
Structure				
Married	0 or 1	0.554	0.690	0.140
Household size	1–3			
Alone	(1)	0.324	0.236	0.569
One other	(2)	0.523	0.663	0.176
2 or more	(3)	0.153	0.101	0.255
Children	1 –4			
0	(1)	0.135	0.097	0.048
1	(2)	0.306	0.274	0.176
2	(3)	0.262	0.290	0.222
≥3	(4)	0.297	0.339	0.554
Network size	1–6	1.711	4.466	3.946
Interaction frequency	0–365	253.162	174.401	212.741
Proportion family	0–1	0.303	0.398	0.706
Network range	0–1	0.988	0.575	0.423
Network density	0–1	0.792	0.652	0.810
Social Engagement				
Attends religious services	0 or 1	0.365	0.494	0.458
Volunteers	0 or 1	0.136	0.237	0.16
Attends local meetings	0 or 1	0.189	0.287	0.214
Function				
Support	1–3	2.205	2.439	2.367
Strain	1–3	1.267	1.291	1.213
Quality				
Loneliness	1–3	1.398	1.330	1.512

Enriched networks

Individuals in this group have broad and robust social networks, with a high marriage rate of 69%, indicating strong family connections. Their average network size is 4.47, but they interact less frequently (174.4 days/year), possibly due to the complexities of managing larger networks. Family members constitute 39.8% of their networks, emphasizing familial ties alongside other relationships. They enhance their social life by participating more in activities like volunteering, attending religious services, and local meetings than other groups. This group reports the lowest levels of loneliness among the 3 network types.

Restricted networks

Individuals in the "Restricted" type have smaller, less supportive social networks, with a low marriage rate of 14%, indicating fewer spousal connections. A significant proportion (56.9%) lives alone. Their network size is 3.95, larger than "Focused" but smaller than "Enriched" networks. A high proportion of their network (70.6%) consists of family members, suggesting a lack of diversity. Notably, members report the highest level of loneliness (1.512) among the 3 network types.

Focused networks

This type consists of individuals with more intimate and potentially supportive networks. They have a moderate marriage rate of 55.4%, but their network size (1.71) is less than half that of the "Enriched" or "Restricted" types. Despite the smaller size, they have a higher interaction frequency (253.2 days/year), indicating regular, meaningful engagements. The balance between family and nonfamily members provides diverse support, leading to more satisfying social experiences and lower loneliness levels compared to the "Restricted" type (1.398 vs 1.512). This suggests that although their circle of confidants is relatively small, members are less lonely than those in the "Restricted" type.

How Does Network Type Membership Change Over Time?

Our analysis involved 3 steps: tracking transitions between network types across rounds, examining membership variations among ethnoracial and linguistic groups, and assessing covariates influencing transitions.

Network evolution

Supplementary Table 4a shows the likelihood of network-type transitions from Round 1 to Round 2. Individuals initially classified as "Focused" had a 34.3% chance of remaining in this category, 43.5% transitioned to "Enriched," and 22% moved to "Restricted." "Enriched" members had a 68.7% chance of maintaining their status, with 14.7% shifting to "Focused" and 16.6% to "Restricted." The "Restricted" type showed the highest persistence, with 87.1% remaining the same, 12.8% moving to "Focused," and only 0.1% shifting to "Enriched."

Supplementary Table 4b shows a similar pattern from Round 2 to Round 3. The "Focused" group had a 43% chance of remaining, 37.1% transitioned to "Enriched," and 20% to "Restricted." "Enriched" members had a 64.5% chance of maintaining their status, with 17.8% moving to "Focused" and 17.7% to "Restricted." The "Restricted" type remained highly persistent, with 85.5% staying the same, 11.5% moving to "Focused," and 3% to "Enriched."

Over time, the proportions of "Focused" and "Enriched" types decreased, whereas the "Restricted" type became increasingly predominant. Figure 2 illustrates that the proportion of individuals in "Restricted" networks doubled between Rounds 1 and 3, largely because individuals in "Restricted" networks rarely transition out, whereas others tend to move into "Restricted" networks as they age.

Network type variations

Table 5 shows odds ratios (OR) from multinomial logistic regressions predicting membership over three rounds, comparing the likelihood of being in the "Focused" versus "Restricted," and "Enriched" versus "Restricted" types. Higher education levels increased the likelihood of belonging to "Focused" or "Enriched" types over "Restricted" in the first 2 rounds. By Round 3, Spanish-speaking Hispanic adults showed significantly reduced odds of being in the "Enriched" type (OR = 0.415, $p < .05$).

At Round 1, all non-White groups were more likely to be in the "Restricted" type compared to the "Enriched" type. Black participants were less likely to be in the "Enriched" type (OR = 0.436, $p < .001$). English-speaking Hispanic adults had lower odds of being in both "Focused" versus "Restricted" (OR = 0.383, $p < .001$) and "Enriched" versus "Restricted" (OR = 0.436, $p < .001$). The "Else" racial category also showed a negative association with being in the "Enriched" type (OR = 0.221, $p < .05$). In later rounds, these trends fluctuated, suggesting selection effects; perhaps only the healthiest or most advantaged individuals from disadvantaged groups remained in the sample.

Women consistently had lower odds of being in the "Focused" or "Enriched" types across all rounds, with this gender effect slightly lessening by Round 3. Baseline age consistently correlated with a higher likelihood of being in the "Restricted" type across all rounds, with the trend strengthening over time.

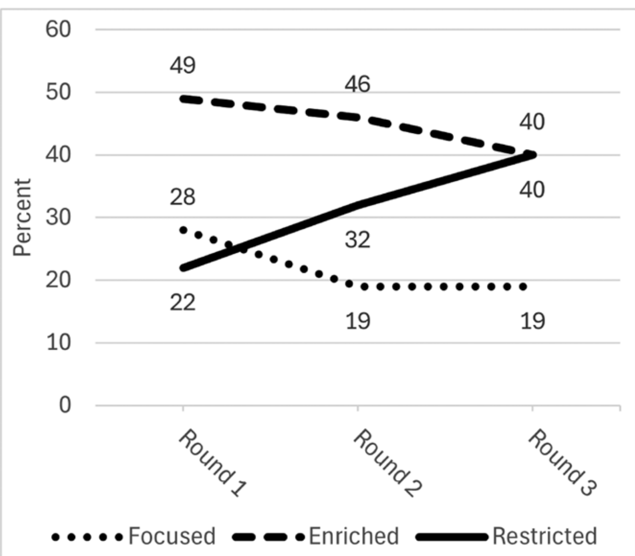

Figure 2. Proportion of respondents by network type and round.

Covariate impact on network transitions

We analyzed factors affecting network-type transitions (Table 6). From Round 1 to 2, higher education reduced the odds of transitioning from "Focused" to "Restricted" (OR = 0.90, $p < .05$) and from "Enriched" to "Restricted" (OR = 0.87, $p < .05$). From Round 2 to 3, education continued to lower the likelihood of moving from "Enriched" to "Focused" (OR = 0.91, $p < .05$).

Female gender increased the risk of moving into the "Restricted" type at both transitions. Older participants were more likely to transition from "Enriched" to "Focused" or "Restricted" types at both points. Black adults were more likely to transition from "Enriched" to "Focused" (OR = 2.81, $p < .05$) or "Enriched" to "Restricted" (OR = 2.36, $p < .05$) during the first transition.

How Do Network Types Relate To SRH?

Using OLS regression analysis (Table 7), we examined the impact of network types on SRH. In Round 1, members of the "Restricted" type rated their health as significantly lower than those in the "Enriched" type (β = − 0.283, $p < .01$). In Round 2, the "Focused" type showed a significant negative association with SRH compared to "Enriched" (β = − 1.84, $p < .01$). In Round 3, both "Focused" (β = − 0.084) and "Restricted" (β = − 0.164) types reported worse SRH than "Enriched," but differences were not significant.

Overall, network type affects SRH variably over time. The "Restricted" type consistently correlates with poorer SRH in Round 1, whereas the "Focused" type affects SRH negatively in Round 2. This variability suggests that dynamic factors not captured here may influence the relationship between network type and SRH over time.

Discussion and Implications

This study analyzed NSHAP data to classify older adults' social networks into 3 types: "Enriched," "Focused," and "Restricted." The "Enriched" group had the largest, most diverse networks (average 4.47 members), high marriage rates (69%), and reported the lowest loneliness levels, aligning with prior research linking larger networks to reduced loneliness and enhanced psychological well-being among older adults (17,67). The "Restricted" group often lived alone, had smaller, less supportive networks (average 3.95 members), low marriage rates (14%), and reported the highest loneliness, consistent with literature connecting restricted networks to increased loneliness and poor health outcomes in later life (18,19). The "Focused" group had the smallest networks (average 1.71 members) and moderate marriage rates (55.4%), but high interaction frequency. They reported less loneliness than the "Restricted" group, suggesting frequent, meaningful interactions can mitigate the negative effects of smaller network size. These findings support research showing older adults' social networks are dynamic and can shift after significant life changes like widowhood, retirement, or health decline (8).

Shifts in network types were observed over time. The proportions of "Focused" and "Enriched" types decreased, whereas the "Restricted" type became more predominant. The "Focused" group showed the most mobility: from Round 1 to Round 2, 43.5% transitioned to the "Enriched" type, indicating increased social engagement, whereas about 22% moved into the "Restricted" type, suggesting a decline in their social networks. Similar patterns emerged between Rounds 2 and 3, with 37.1% moving to the "Enriched" type and 20% into the "Restricted" type.

This mobility is puzzling given Cornwell et al. (2020) found older adults' networks generally remain stable despite turnover (68). One explanation is that individuals with smaller networks may be more vulnerable to transitioning into "Restricted" networks, especially after losing a spouse or close family member. Cornwell (2015) also found that African Americans and low socioeconomic status individuals struggled more to replace confidant losses, resulting in higher rates of network shrinkage, partly explained by factors like poorer health and higher widowhood rates, but much remains unexplained (27).

The increasing prevalence of "Restricted" networks over time highlights the challenges older adults face in maintaining social connections. However, mobility within the "Focused" group shows promise: in each round, more moved into the "Enriched" group than into the "Restricted" group. This suggests many older adults can enrich their networks as they age, aligning with research showing transitions into more diverse networks lower mortality risks (69). Factors driving these shifts warrant further investigation to inform interventions promoting social connections, especially for vulnerable groups.

In contrast, the "Restricted" type demonstrated the highest persistence, with over 85% maintaining their status between rounds. Few transitioned to a better-connected network, typically moving into the "Focused" type; transitions into the "Enriched" type were rare, highlighting significant barriers like limited social opportunities, poor health, or socioeconomic challenges. The "Enriched" type showed considerable stability, with about two-thirds maintaining their status between rounds. However, transitions into "Focused" and "Restricted" types were not uncommon, indicating that even well-established networks can be disrupted by adverse life circumstances like loss of a spouse or declining health.

Demographic factors influenced network membership. Black and Hispanic adults were more likely to be in the

Table 5. Multinomial Logistic Regressions Predicting Network Type, Over All 3 Rounds (odds ratios).

Variable	Round 1		Round 2		Round 3	
	Focused vs Restricted	Enriched vs Restricted	Focused vs Restricted	Enriched vs Restricted	Focused vs Restricted	Enriched vs Restricted
Education (years)	1.041	1.162***	1.105**	1.150***	0.961	1.051
Female	0.284***	0.463***	0.379***	0.595*	0.463	0.477**
Race						
White (Ref.)						
Black	1.391	0.436***	1.185	0.423**	1.462	1.062
Hispanic, English	0.383***	0.436***	1.209	0.741	0.691	0.375
Hispanic, Spanish	1.020	0.449*	1.350	1.649	0.589	0.415*
All Else	0.391	0.221*	1.041	0.844	1.073	0.395
Age at R1	0.756**	0.741*	0.827	0.613*	0.560**	0.383***

***$p < .001$. **$p < .01$. *$p < .05$.

Table 6. Predicted Transitions Between Network Types (odds ratios)

Variable	Round 1 → Round 2			Round 2 → Round 3		
	Focused → Restricted	Enriched → Focused	Enriched → Restricted	Focused → Restricted	Enriched → Focused	Enriched → Restricted
Education (years)	0.90*	0.96	0.87*	1.04	0.91*	0.95
Female	2.65*	0.64*	1.68*	2.15*	0.97	2.10*
Race						
White (Ref.)						
Black	0.84	2.81*	2.36*	0.68	1.38	0.94
Hispanic, English	0.83	1.64	1.35	1.45	1.83	2.66
Hispanic, Spanish	0.74	0.82	0.61	1.69	1.42	2.40
All Else	0.96	1.24	1.19	0.93	2.73	2.54
Age at R1	1.21	1.35*	1.64*	1.78*	1.47*	2.62*

***$p < .001$. **$p < .01$. *$p < .05$.

Table 7. Network Type Membership Predicting Self-Rated Physical Health

Variables	Round 1	Round 2	Round 3
Enriched (Ref.)			
Focused	−0.055	−1.84**	−0.084
Restricted	−0.283**	−0.39	−0.164

***$p < .001$.**$p < .01$.*$p < .05$.

"Restricted" type. In Round 1, Black participants were less likely to be in the "Enriched" type (OR = 0.436, $p < .001$). English-speaking Hispanic adults also had lower odds of being in "Focused" versus "Restricted" (OR = 0.383, $p < .001$) and "Enriched" versus "Restricted" types (OR = 0.436, $p < .001$). Although significance diminished over time, initial affects underscore the influence of race and ethnicity on social network formation and stability, echoing research on structural inequalities limiting social integration among minority older adults (27).

Gender, age, and education also shaped social network types. Women consistently had lower odds of belonging to the "Focused" or "Enriched" types throughout all rounds. This appears to counter literature showing older women maintain larger networks and report less loneliness than men (7). However, social network types are characterized by a constellation of factors, not solely by network size or loneliness (8). "Restricted" networks have higher kin concentration, lower marriage rates, greater network density, and higher loneliness—characteristics relevant for women who are more likely to outlive spouses and assume caregiving roles due to gendered expectations (70). The lower odds of women belonging to the "Focused" or "Enriched" networks may reflect structural disadvantages in social capital stemming from lifelong gendered roles and expectations. Research shows men benefit more from work-based and community networks, whereas women's networks tend to be more kin-centric, partly due to caregiving responsibilities, limiting access to diverse social opportunities (71).

Education played a role: higher education levels were associated with a greater likelihood of being in "Focused" or "Enriched" types, reflecting the link between education and social capital, where higher education facilitates maintaining or expanding networks (71). For Spanish-speaking Hispanic adults—who tend to have the lowest education levels among the groups analyzed—language and education may have a compounding effect, reducing the odds of being in the "Enriched" type (OR = 0.415, $p < .05$) by Round 3. Language and cultural barriers may make rebounding from age-related losses particularly challenging.

Baseline age was consistently related to a higher likelihood of being in the "Restricted" type, indicating older cohorts were more prone to remaining in or transitioning to "Restricted," with this trend strengthening over time. These results underscore the interplay between social network composition and societal inequalities, where disparities in education, gender dynamics, and age-related factors converge to influence social connectedness in later life.

Lastly, we assessed the impact of network type membership on older adults' SRH and found that network type variably affects SRH over time, with the "Restricted" type consistently linked to poorer SRH in Round 1 and the "Focused" type significantly affecting SRH in Round 2. By Round 3, both the "Focused" (β = −0.084) and "Restricted" (β = −0.164) types continued to report worse SRH compared to the "Enriched" type, but without significant differences. These trends are consistent with other research that examines the association between restricted network profiles and health outcomes (54,69,72). Studies show sustained restricted networks are associated with increased mortality risk compared to diverse profiles, and transitions from restricted to diverse profiles can lower mortality risk (69,72).

This study has limitations. Relying on SRH as the primary outcome may not fully capture overall health status or other well-being aspects. The longitudinal observational design cannot establish causality between social network types and health outcomes. The variability in effects suggests unmeasured dynamic factors might influence the relationship between network type and SRH, highlighting the complexity of how social connections affect older adults' health.

For instance, personality traits like extraversion and agreeableness significantly affect one's ability to maintain and expand social networks, potentially affecting health outcomes (73,74). Another limitation is the diminishing significance of race and ethnicity in predicting network membership over time, indicating that unmeasured factors, such as selection effects, might influence evolving social networks among older adults. This trend may reflect underlying processes like neighborhood effects, health selection into different networks, or changes in social engagement due to declining health. Evidence shows that neighborhood context can contribute to disparities in access to network-based resources (75).

Despite limitations, this study provides insights into the dynamics of social networks among older adults and their impact on health. Using RI-LTA allowed for in-depth analysis of transitions as a latent variable, revealing how social network characteristics evolved. The persistence and expansion of the "Restricted" network over time indicate that individuals entering this category often remain, with more participants joining. This trend is particularly relevant to health inequities, as factors like race, ethnicity, language, gender, and age converge to influence health outcomes and social support access. The negative health outcomes associated with the "Focused" and "Restricted" types highlight the crucial role of social networks in addressing health disparities.

Future research should expand on these findings by including a broader range of health indicators, investigating causal mechanisms, and examining how interventions could enhance social connectivity and health among older adults. Interventions designed to broaden and enrich the social networks of older adults could yield substantial health benefits, especially for those in disadvantaged groups. Understanding these dynamics can inform policies and programs that tackle social isolation and enhance health equity among aging populations.

Supplementary Material

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

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Conflict of Interest

None.

Data Availability

NSHAP data are available in the National Archive of Computerized Data on Aging at the Inter-University Consortium for Political and Social Research, accessible at https://www.icpsr.umich.edu/web/NACDA/series/706. The study was not preregistered.

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