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Associations between social network characteristics and daily social experiences in later life: evidence from ecological momentary assessment

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Abstract

Objectives: **Sociological theory posits that social networks function as enduring relational structures that constrain and enable everyday social interactions, yet empirical evidence linking network properties to real-time social exposures remains limited. To address this gap, this study examines how older adults' social networks are associated with their daily social experiences.**

Methods: **Using data from the Social Environment and Cognitive Health in Urban and Rural Areas (SECHURA) study, we combine egocentric network data (1,474 alters from 254 respondents) with ecological momentary assessment (EMA) data capturing real-time social interactions over one week (5,342 observations). We evaluate associations between three network properties–structure (quantity, composition, and interconnectedness of network members), heterogeneity (diversity in gender, race/ethnicity, and age), and strength (strong and supportive ties)—and four momentary outcomes (number and type of interaction partners, social activities, and being outside the home).**

Results: **Random-effects models show that larger and more socially diverse networks are associated with greater momentary social engagement, including more interaction partners, less time alone, and more explicit socializing. Both role diversity and network density are associated with heightened social exposure, through distinct pathways. Sociodemographic heterogeneity also predicts interaction patterns, with age heterogeneity linked to kin-centered interactions and racial heterogeneity to non-kin exposure. Stronger affective ties predicted less engagement in explicit socializing.**

Discussion: **Personal social networks operate as critical structures linked to the quantity, composition, and context of older adults' real-time social exposures. Large, densely connected, and role-diverse networks appear to facilitate everyday interactions through different mechanisms.**

Keywords: Social networks, Social interaction, Network structure, Momentary ecological assessment, Social activities, Successful aging

Research suggests that social networks offer opportunities and impose constraints on everyday social interactions (Burt, 2000; Granovetter, 1973; Simmel, 1950; Wellman, 1988), reflecting relational patterns that condition the everyday flow of social contact, support, information, and resources. In other words, social networks represent enduring, aggregate social structures that can be activated in daily life to shape a range of social experiences, including how many social interactions occur, who people interact with, and how and where they spend their time. These everyday experiences, in turn, are linked to momentary affect, stress, and loneliness, which may accumulate to shape health and well-being (Goldman & York Cornwell, 2023; Zhaoyang et al., 2024). This study uses social network analysis and ecological momentary assessment (EMA) to examine how older adults' personal networks associate with their daily social experiences.

Social network theory

We conceptualize personal social networks as relatively stable, meso-level relational structures that are measured in our study prior to real-time interactions captured via EMA. Personal networks are therefore temporally and analytically antecedent to

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momentary interactions. Within this design, we test theories asserting that network structure enables and constrains momentary social experience. Specifically, we examine whether the structure, composition, and strength of a person's network are associated with the frequency, partner types, activities, and settings of their everyday social interactions. Network theory suggests this relationship is likely reciprocal, wherein repeated social interactions aggregated over long periods of time constitute and reinforce personal network ties. This bidirectional relationship is consistent with Feld's (1981) theory of focused activity, in which relationships form and are sustained through repeated contact organized around shared foci of activity (Feld, 1981, 1982). However, because our network data reflect a single baseline assessment, reciprocal pathways cannot be tested and are treated as a theoretical implication of our findings rather than an empirical claim.

Broadly, we draw on two foundational theoretical concepts from social networks. First, *social bridging* captures resources associated with being embedded in an expansive, loosely connected network of socially diverse contacts, such as neighbors, coworkers, and casual friends, who span different social groups (Burt, 2000; Coleman, 1988; Granovetter, 1973). This pattern reflects Burt's (2000) theory of structural holes, in which gaps between otherwise unconnected network members position the focal individual as a broker across distinct social worlds. Bridging derives benefit not from depth of connection but from reach: irregular contact with a heterogeneous set of peripheral others exposes individuals to novel ideas, information, activities, and resources beyond what a smaller, more homogeneous core network would typically offer (Burt, 2000; Granovetter, 1973; Lin, 2002).

Second, *social bonding* reflects resources derived from integration in a tightly knit network of close, trusted, and often kin-based relationships (e.g., spouse, family members, and close confidants) (Berkman et al., 2000; Claridge, 2018; Coleman, 1988; Lin, 2002). Bonding is facilitated by what Coleman (1988) terms network closure, where one's contacts are also connected to one another, enabling trust, enforcement of social norms, and reciprocal obligation. Where bridging emphasizes breadth and novelty, bonding emphasizes depth and interconnectedness. Individuals with networks high in social bonding benefit from a reliable source of companionship, emotional support, and instrumental assistance, alongside meaningful social roles, such as spouse or parent, that foster a sense of security, mattering, and belonging.

As opposing mechanisms, bridging and bonding shape our expectations for how social network characteristics relate to momentary social interactions. We organize our analysis around three characteristics: network structure, heterogeneity, and tie strength. *Network structure* refers to the quantity, composition, and interconnectedness of members of a network, or alters. At the most basic level, having a larger network increases the potential pool of regular interaction partners who can initiate or receive contact and who can invite or be available for shared activities. Likewise, having a network that contains social roles beyond the family (e.g., friends, coworkers, and neighbors) may promote sociality by providing exposure to multiple, distinct social worlds. Finally, a network that is loosely interconnected and contains multiple separate components (i.e., structural holes) may provide access to non-redundant socializing opportunities outside the home (Burt, 2000; Coleman, 1988; Cornwell, 2009). In general, networks that are large, contain a diversity of social roles, and are less densely connected may shape sociality with a greater number and diversity of interaction partners through their bridging properties.

Network heterogeneity refers to the degree of variation among alters in a network with respect to social, demographic, or other characteristics (Perry et al., 2018). Here, we focus on gender, race, and age. Networks that are more heterogenous with respect to these characteristics may connect older adults to different kinds of activities, social groups, and cultural opportunities, increasing both the number and diversity of social interactions and interaction partners (Blau, 1977; Burt, 2000; McPherson et al., 2001). Similar to bridging, heterogeneity implies less redundancy, meaning that people are exposed to greater novelty in social interactions, may receive more varied invitations for social engagement, and are more frequently pulled into public spaces (Ellwardt et al., 2015; McPherson et al., 2001; Perry et al., 2018). Similar to the structural measures described above, networks with greater sociodemographic heterogeneity likely operate through bridging mechanisms.

Network strength, or the intensity, quality, or functional capacity of social connections within a network (Perry et al., 2018), may also condition everyday social exposures. Networks that are affectively closer and more supportive may promote an inward-facing orientation and interactions with a smaller number of core network ties, such as close kin (Wellman & Wortley, 1990). However, older adults with stronger and more supportive networks might also have more total interactions, especially if alters are geographically close. That is, strong-tie networks might be more proximate (e.g., cohabitating) and thus more likely to be activated for meaningful face-to-face interactions, including supportive exchanges, shared activities, and reciprocal obligations. Measures of tie strength are likely to operate via bonding mechanisms, facilitating network closure as opposed to reach (Coleman, 1988).

Momentary social interactions

To evaluate older adults' everyday social exposures, we perform repeated real-time sampling in naturalistic settings using EMA (Browning et al., 2024). This method is well-suited to understanding daily social patterns of behavior and interaction (Roth, 2024) while minimizing bias and recall errors associated with global, retrospective, static reports of older adults' routine experiences commonly used in aging research (Cain et al., 2009). Additionally, EMA studies have shown significant within-person variation in perceptions of social isolation and loneliness, suggesting that these are not entirely static traits, but rather depend at least in part on momentary conditions, such as whether someone is alone and at home (Compernolle et al., 2021; Peng & Roth, 2025; Shi et al., 2024).

In parallel, recent time-diary research shows Americans spending increasingly more time at home and alone over the past two decades, a trend that predates and outlasted COVID-19 (Atalay, 2024; Sharkey, 2024). Each additional hour spent at home is associated with more time alone and less time with friends (Sharkey, 2024). The home is simultaneously the largest

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source of daily social contact for those who cohabitate with family, friends, or roommates and the greatest source of social isolation for older adults living alone (Peng, 2025). These patterns motivate our focus on number of interaction partners, partner type, social activities, and location as EMA outcomes. Specifically, these outcomes capture the dimensions of momentary interactions and social time use driving trends in social isolation.

Moreover, recent studies have linked EMAs to short-term health outcomes, such as positive affect and a lower likelihood of stress, pain, and fatigue, even net of measures of social connectedness such as network size and perceived social support (Bernstein et al., 2018; Goldman & York Cornwell, 2023; Shi et al., 2024). Similarly, time-diary research finds that momentary positive affect varies by companionship, with people reporting greater enjoyment while socializing and with friends, relatives, and spouses than while alone, independent of global wellbeing reports (Kahneman et al., 2004). These studies demonstrate complex relationships between perceived measures of global connectedness, momentary conditions, and health and wellbeing. They also support the need for additional research on real-time social exposures that reflect the everyday lived experience of social connectedness.

The present study

Despite the importance of momentary interactions for perceptions of one's social world and for health and wellbeing, minimal research has examined the broader social conditions from which they arise. Network theory suggests that social networks both constrain and enable opportunities for everyday social interactions (Burt, 2000; Granovetter, 1973; Simmel, 1950; Wellman, 1988), yet we lack empirical evidence on how global network characteristics structure momentary interactions in daily life (for an exception, see Goldman & York Cornwell, 2023). Similarly, time use research on where and with whom U.S. adults spend their day has focused on physical and institutional contexts, such as home, workplace, and third places, without considering how personal networks shape these patterns (Peng, 2025). This is an important gap since social networks are a stable but modifiable protective factor for addressing social isolation and loneliness among vulnerable older adults (Hansen et al., 2024; Roth, 2020). To address this gap, using EMA and social network data from a state-representative sample of older adults, we examine associations between three network properties (structure, heterogeneity, and strength) and four EMA outcomes over a subsequent one-week period: number of interaction partners, partner type, social activity engagement, and being outside the home.

Data and methods

This study employed data from the Social Environment and Cognitive Health in Urban and Rural Areas (SECHURA) study, a state-representative probability sample of Indiana residents aged 55 and older designed to examine how social context is linked to cognitive health across urban and rural settings. SECHURA is particularly well suited for this analysis because it combines detailed person-level information on social networks with repeated, real-time measures of activities and social interactions collected via EMA. Between November 2023 and March 2024, 510 respondents enrolled in the SECHURA study and completed a computer-assisted personal interview (CAPI; response rate = 67%). The CAPI included a personal network module as well as measures of sociodemographic characteristics, health, and social engagement. Detailed documentation of the SECHURA study design is provided in Roth et al. (2026).

Dependent variables

We examined four interaction-level outcomes derived from EMA reports to capture the quantity, composition, activity, and setting of respondents' real-time social interactions. A detailed description of EMA procedures is provided in Text S1. All dependent variables were measured at the EMA-interaction level.

Number of interaction partners

At each EMA prompt, respondents were asked, "When you heard the notification, approximately how many people were you interacting with?" Responses captured the number of individuals present at the moment of each EMA and ranged from zero (no one present) to as many as 200 people. The distribution was highly right-skewed, reflecting zero inflation in conjunction with a few reports involving very large groups. To limit the influence of extreme values, and because it was unlikely that a respondent could engage in meaningful interaction with everyone in a very large group simultaneously, this count variable was top-coded at 15, yielding a range from 0 to 15.

Type of interaction partner

At each EMA prompt, respondents were asked, "When you heard the notification, who was with you?" and could select all applicable relationship types from a predefined list. Critically, this item did not ask about specific named individuals and was not restricted to, or cross-referenced with, the personal network roster. We constructed a categorical indicator capturing the type of interaction partner, distinguishing interacting alone, with kin, or with non-kin. Kin included family members by blood or marriage (e.g., spouse/romantic partner, sibling, child, and other relatives), while non-kin included friends, coworkers, neighbors, organizational contacts, acquaintances, and strangers (see full list in Table S3). Respondents could report multiple partner types within a single EMA, but those involving a combination of kin and non-kin were very rare (3.54% of EMAs, $n = 189$). To avoid this small cell size, we imposed a hierarchical coding scheme that prioritized the weakest social tie present. For example, interactions involving any non-kin were coded as non-kin; interactions involving kin, but no non-kin, were coded as kin. As a sensitivity check, we created this variable using an alternative coding scheme that prioritized the strongest social tie present, as well as a four-category variable reflecting alone, kin only, non-kin only, and mixed kin/non-kin interactions.

Explicit socializing

At each EMA, respondents reported their current activity from a predefined list of ten categories (e.g., eating or drinking, working, household chores, volunteering, and transportation). Based on these responses, we constructed a binary indicator capturing whether the respondent was engaged in explicit socializing

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(coded 1) versus not (coded 0), distinguishing explicitly social activities from entertaining or task-oriented ones that happen to occur in the presence of others (e.g., working with a coworker). The response options for the original variable were from the American Time Use Survey (ATUS) WHAT question, which asked respondents what they were doing at a given time. For our instrument, we retained the most popular options and collapsed less frequently mentioned ATUS activities to fit the response options on a phone screen for EMA administration. See Table S3 for the full list of activities respondents could choose from.

Outside the home

Respondents reported their physical setting at the time of each EMA from predefined categories (e.g., home, workplace, restaurant, and public space; see Table S3). We constructed a binary indicator distinguishing interactions that occurred at home (coded 0) from those occurring outside the home (coded 1), capturing exposure to social contexts beyond the household.

Independent variables

We examined three sets of independent variables derived from the personal network protocol to capture network structure, heterogeneity, and strength of ties among core support networks. A detailed description of the personal social network protocol is provided in Text S1. All independent variables were measured at the respondent level.

Network structure

Three common measures of network structure were included in multivariate models: network size, density, and diversity. *Network size* (i.e., degree) is the total number of unique network members named in response to all name generators. An egocentric measure of *network density* was calculated as the average tie strength (range = 0-3) between network members (i.e., alter-alter ties). *Network diversity* is the total number of unique social roles present in the network (e.g., spouse, child, neighbor, and coworker).

Network heterogeneity

We examined the effects of three indicators of heterogeneity, or sociodemographic diversity, in the personal network. We included a measure of gender heterogeneity, Blau's Index, using the following formula, where p is the proportion in each gender category:

$$Blaú\ \ Index = 1 - (p^2_{women} + p^2_{men}).$$

Blau's Index for two categories ranges from 0 to 0.5, where 0 indicates that all network members are in the same gender category and 0.5 indicates that the network is perfectly balanced between men and women. Only seven alters out of 1,474 were described as transgender ($n = 2$), non-binary ($n = 2$), or queer ($n = 3$), resulting in a highly skewed Blau's Index for a few observations. A prior analysis using all six gender categories to calculate the gender heterogeneity measure produced substantively similar results. However, the small cell sizes precluded reliable inference.

Consequently, these were temporarily coded as missing only for the calculation of Blau's Index to retain the two-category formula and to avoid a small number of high-influence observations. In addition, we measured racial heterogeneity in the network using a binary variable: 1 if two or more races are present, and 0 otherwise. We used this approach due to minimal racial heterogeneity, resulting in a severely right-skewed Blau's index for race. Finally, we measured age heterogeneity by calculating the standard deviation (SD) of alters' ages in years.

Network strength

We included two variables measuring network strength. *Mean tie strength* is the average strength of ties between the focal person (i.e., ego) and each of their network members on a 1-10 scale. *Mean support function*, the average count of different types of support provided by each alter (theoretically ranging from 0 to 5), was calculated using five types of received support (yes or no): expressing care, listening, providing advice, providing instrumental support (e.g., help with chores), and giving or loaning money.

Covariates

We included a robust set of covariates in multivariate models to address potential confounding factors. For respondent demographics, we included age in years, gender (man or woman), race (White or non-White), education (less than high school, high school or GED, some college or technical school, or college graduate), whether the respondent is currently working either full- or part-time (yes or no), and whether they are currently married *versus* separated, widowed, divorced, or single (yes or no). To adjust for health issues that could impact both social network characteristics and daily activities and interactions, we further controlled for depressive symptoms using the 15-item Geriatric Depression Scale (Sheikh & Yesavage, 1986) and for functional activity limitations measured using a 10-item scale (e.g., assembling tax records, buying groceries, heating water, preparing a meal, and traveling out) (Pfeffer et al., 1982). Finally, we adjusted for the average number of EMAs completed per day, whether the EMA occurred in the morning prior to noon (*vs* afternoon or evening), and on a weekend (*vs* a weekday).

Analysis

Of the 273 respondents who participated in the EMA module, 19 were excluded due to missing data on key variables, including personal network characteristics and sociodemographic covariates. We also removed 88 EMA prompts that were completed more than 30 min after being issued. To construct the personal-level network variables, respondents needed to nominate at least one alter in the networks. Applying this criterion yielded a final analytic sample of 254 respondents and 5,342 valid EMA observations.

First, we presented descriptive statistics for all variables in these analyses. We next used random-effects regression for longitudinal data to account for within-person clustering of EMAs. We estimated random-effects models rather than fixed-effects or population-averaged alternatives because our research question required decomposing real-time social experience into

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Table 1 Descriptive statistics.

Variables	Response	Mean (*SD*)	Range	%
EMA-level variables ($N = 5{,}342$)[a]				
Number of interaction partners (truncated at 15)		0.98 (2.15)	0–15	
Type of interaction partner[b]	Alone			60.30
	Kin			22.37
	Non-kin			17.33
Type of activity	Explicit socializing (1)			9.25
	Not socializing (0)			90.75
Setting	Away from home (1)			29.24
	Home (0)			70.76
Daily Window when EMA was administered	Morning (1)			22.89
	Afternoon/evening (0)			77.11
Day type	Weekend (1)			28.08
	Weekday (0)			71.92
Network characteristics ($N = 254$)[c]				
Network size		5.80 (2.88)	2–17	
Network diversity		2.12 (0.77)	1–4	
Network density		1.72 (0.79)	0–3	
Gender heterogeneity		0.35 (0.16)	0–0.5	
Any racial heterogeneity			0–1	23.39
Age heterogeneity		14.88 (6.93)	0–48.08	
Mean tie strength		8.53 (1.20)	4.75–10	
Number of support functions		3.64 (0.88)	1–5	
Respondent characteristics ($N = 254$)[c]				
Age (in 10 years)		6.72 (0.77)	5.3–8.8	
Gender	Woman			70.47
	Man			29.53
Race	White			91.73
	Non-White			9.27
Educational attainment	High school or less			22.83
	Some college			33.86
	College or more			43.31
Currently working either full-time or part-time	Yes			35.83
	No			64.17
Currently married	Yes			49.61
	No			50.39
Geriatric depressive symptoms		2.82 (2.79)	0–14	
Functional activity limitations		1.61 (2.94)	0–21	
Average daily EMA completion		3.32 (0.85)	1–4	

Note. SD = standard deviation; EMA = ecological momentary assessment.
[a]Percentages for EMA-level variables were calculated based on all EMAs in the analytic sample.
[b]Respondents could have reported being with multiple types of interaction partners per EMA session. We coded the "with whom" variable hierarchically, prioritizing the weakest tie when multiple partners were present.
[c]Network, psychological, and sociodemographic variables were calculated at the respondent level.

within-person and between-person components. Preliminary intraclass correlation estimates (ICC = 0.13-0.24 across outcomes) indicated meaningful variance at both within- and between-person levels, underscoring the value of using a modeling framework capable of distinguishing them.

For the count outcome (number of interaction partners), we used random-effects negative binomial regression because the data were overdispersed. Results were reported as incidence rate ratios (IRRs). Dichotomous outcomes (social activity and outside the home) were analyzed using random-effects binary logistic regression models, with odds ratios (ORs) reported. For the multinomial outcome, type of interaction partner, we used random-effects multinomial logistic regression and reported relative risk ratios (RRR) in tables, with "alone" as the comparison category for "kin" and "non-kin." In all regression models, we entered sets of conceptually related network variables in a stepwise fashion to avoid multicollinearity resulting from including multiple correlated variables in a single model. Finally, to facilitate interpretation of these non-linear models, we calculated average marginal effects (AMEs) for social network variables, adjusting for all covariates. Results were presented as the average change in predicted probabilities associated with a 1-SD

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Table 2 Two-level negative binomial random-effects models predicting the number of interaction partners per EMA interaction, $N = 5,342$.

Variables	Model 1	Model 2	Model 3
Woman (ref: man)	1.147 [0.995,1.322]	1.206* [1.043,1.394]	1.153 [0.999,1.331]
Age (in 10 years)	0.795*** [0.719,0.878]	0.812*** [0.735,0.898]	0.801*** [0.724,0.886]
White (ref: non-White)	0.982 [0.775,1.244]	1.011 [0.797,1.282]	1.002 [0.792,1.269]
Some college (ref: high school or less)	1.000 [0.841,1.189]	1.031 [0.864,1.230]	0.984 [0.825,1.173]
College (ref: high school or less)	1.131 [0.952,1.345]	1.191* [1.001,1.416]	1.160 [0.974,1.382]
Currently working (ref: no)	0.876 [0.750,1.022]	0.877 [0.753,1.022]	0.882 [0.757,1.028]
Currently married (ref: no)	1.707*** [1.495,1.949]	1.742*** [1.519,1.997]	1.747*** [1.529,1.996]
Depression symptoms	0.973* [0.948,1.000]	0.965** [0.939,0.991]	0.965* [0.939,0.992]
Functional limitations	1.030* [1.004,1.056]	1.036** [1.010,1.064]	1.028* [1.002,1.054]
Network size	1.045*** [1.020,1.071]		
Network diversity	1.154** [1.041,1.279]		
Network density	1.193*** [1.083,1.314]		
Gender heterogeneity		1.180 [0.794,1.755]	
Any racial heterogeneity		1.309*** [1.126,1.522]	
Age heterogeneity		1.012* [1.003,1.022]	
Mean tie strength			0.951 [0.898,1.007]
Number of support functions			1.031 [0.957,1.112]
Morning (ref: afternoon/evening)	0.649*** [0.581,0.724]	0.649*** [0.582,0.724]	0.649*** [0.582,0.724]
Weekend (ref: weekday)	1.051 [0.960,1.151]	1.056 [0.965,1.157]	1.057 [0.965,1.157]
Average daily EMA completion	1.023 [0.961,1.089]	1.029 [0.967,1.095]	1.025 [0.964,1.091]
Log of the overdispersion parameter	4.456*** [3.451,5.753]	4.179*** [3.248,5.375]	4.271*** [3.317,5.499]

Note. EMA = ecological momentary assessment. Incidence rate ratios with 95% confidence intervals in brackets are reported.
*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

change in each predictor. To ensure comparability of effect sizes, we standardized all non-binary network indicators.

In addition, we conducted seven sets of sensitivity analyses to ensure the robustness of our findings to alternative coding and modeling decisions. These analyses addressed potential selection into EMA participation, the zero-inflated distribution of interaction-partner counts, alternative coding of interaction-partner type, examination of additional network variables, adjustment for rural-urban context, and joint modeling of network variables. Across these specifications, the direction and significance of key network associations with EMA outcomes remained substantively unchanged. Full descriptions results, and discussion are provided in Text S2 and Tables S1–S14.

Results

Descriptive statistics

Descriptive statistics for the analytic sample are presented in Table 1. On average, respondents were 67.2 years old ($SD = 7.7$). About 70% were women and 92% identified as White. Nearly half (43%) held a college degree or higher, and about one third (36%) were currently working. About 50% of the sample was currently married. Overall, the sample is fairly healthy, with a mean of 2.8 ($SD = 2.8$) depressive symptoms and mean functional limitations of 1.6 (SD = 2.9).

On average, respondents nominated 5.8 core network members ($SD = 2.9$; range = 2-17) containing about 2.1 distinct types of relationships ($SD = 0.8$) and with moderately dense ties between alters (mean tie strength of 1.7 on a 0-3 scale; $SD = 0.8$). This suggests respondents had a substantial number of core ties that vary in relationship type, with most being family members and friends, but not all of whom have close ties to one another. We identified fairly high gender heterogeneity, with an average Blau's Index of 0.4 ($SD = 0.2$) out of 0.5, and substantial age heterogeneity, with a mean SD of alter age of 14.9 years ($SD = 6.9$). However, only 23% of networks contained any racial heterogeneity, with the majority being single-race. Overall, these core networks contained strong ties, on average, with a mean tie strength of 8.5 on a 1-10 scale ($SD = 1.2$) and an average of 3.6 out of five support functions ($SD = 0.9$) received by respondents.

For momentary interactions, the mean number of interaction partners reported at any given observation was about 1.0 ($SD = 2.2$), but this variable was right-skewed with a median value of 0 and an interquartile range of 0-1 (see Figure S1 for a histogram depicting the distribution of this variable). Further, when respondents responded to EMAs, they were alone an average of 60% of the time, with a family member 22% of the time, and with someone outside their family 17% of the time. They reported being engaged in an activity explicitly defined as socializing 9% of the time–a category which did not necessarily capture all types of social interaction (e.g., working with coworkers and eating with a spouse). Finally, respondents were away from home during 29% of EMA reports, about 77% of which occurred during the evening or night and 28% on a weekend.

Multivariate models

Table 2 presents IRRs from negative binomial random-effects models predicting the number of people respondents were interacting with during any given EMA. As shown in Model 1, each one-person increase in network size was associated with a

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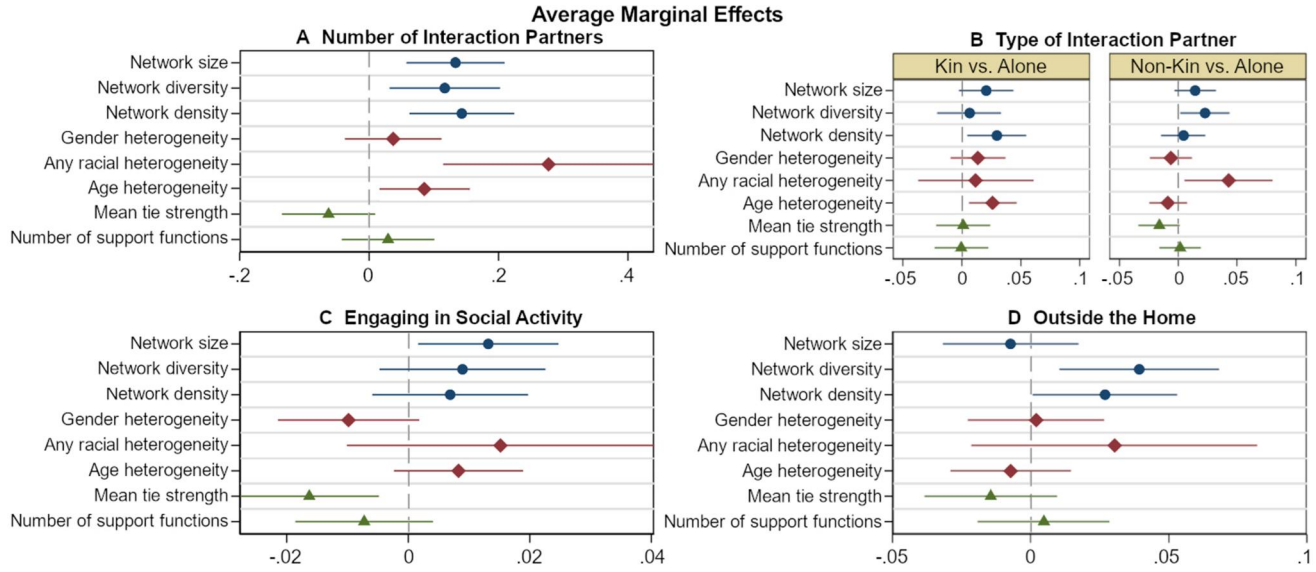


Figure 1 Average marginal effects (AMEs) of network characteristics on real-time social interactions. Network characteristics are standardized to facilitate comparison of AMEs, with the exception of racial heterogeneity, which is a dichotomous indicator. AMEs with confidence intervals that do not overlap zero are statistically significant.

5% increase in the expected number of interaction partners (IRR = 1.05, $p < .001$). Further, each additional social role represented in the network was associated with a 15% increase in the expected number of interaction partners (IRR = 1.15, $p < .01$), while greater strength of ties between alters was also significantly associated with being in the company of more people in the moment (IRR = 1.19, $p < .001$). For network heterogeneity (Model 2), having any two people of different races in one's network was associated with a 31% higher expected count of interaction partners present during an EMA (IRR = 1.31, $p < .001$), while greater age heterogeneity also significantly predicted interacting with a larger number of people (IRR = 1.01, $p < .05$). Finally, neither mean tie strength nor mean number of support functions were significantly associated with the number of interaction partners (Model 3). These patterns were consistent when presented as AMEs (Figure 1, Panel A), with larger, more diverse, and more densely connected networks that were heterogenous with respect to race and age being associated with a higher predicted number of interaction partners, on average.

RRRs from multinomial random-effects regression models are presented in Table 3. As shown in Model 1, being embedded in a larger network was associated with a higher likelihood of being in the presence of kin (RRR = 1.06, $p < .05$) and non-kin (RRR = 1.06, $p < .05$) compared to being alone. Each additional social role represented in a person's network was associated with a 28% increase in the odds of being in the presence of someone outside their family (RRR = 1.28, $p < .05$), such as a friend, coworker, or neighbor, relative to being alone. Also, respondents with dense and closely interconnected networks were more likely to be in the presence of family members (RRR = 1.34, $p < .05$) compared to being alone. Greater age heterogeneity was associated with a higher likelihood of being in the presence of a family member (RRR = 1.03, $p < .05$) compared to being alone (Model 2). Further, having any two people of different races in one's network was associated with a 45% higher likelihood of being in the presence of a non-kin interaction partner (RRR = 1.45, $p < .05$) relative to being alone. Finally, neither mean tie strength nor mean number of support functions were significantly associated with being in the company of kin or non-kin compared to being alone (Model 3). These patterns were largely consistent when presented as AMEs (Figure 1, Panel B), with denser and age-heterogenous networks being associated with greater predicted probability of being with kin *versus* alone, and those that were diverse with respect to social roles and race predicting a higher probability of being in the company of non-kin *versus* alone. However, the AMEs for network size were only marginally significantly different from zero ($p < .10$).

Models 1-3 in Table 4 present ORs from binary logistic random-effects models predicting explicit socializing *versus* other activities. Each one-person increase in network size was associated with 6% higher odds of explicit socializing *versus* doing some other kind of activity (OR = 1.06, $p < .05$; Model 1). Additionally, greater gender heterogeneity in the network significantly predicted lower odds of explicit socializing (OR = 0.39, $p < .05$; Model 2), as did having stronger ties (OR = 0.83, $p < .001$; Model 3), on average. These patterns were largely consistent when presented as AMEs (Figure 1, Panel C), with larger networks and weaker networks associated with a higher predicted probability of explicit socializing. However, the AMEs for gender heterogeneity were only marginally significantly different from zero ($p < .10$).

Findings from binary logistic random-effects models predicting being outside the home in real time are also presented in Table 4 (Model 4-6). As shown in Model 4, each additional social role represented in the network was associated with 34% higher odds of being outside the home (OR = 1.34, $p < .01$), while greater density of close ties between alters was also associated with spending time not at home (OR = 1.22, $p < .05$). No measures of sociodemographic heterogeneity or network strength were significantly associated with time spent outside the home

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Table 3 Two-level multinomial random-effects models predicting type of interaction partner per EMA interaction, $N = 5{,}342$.

Variables	Model 1		Model 2		Model 3	
	Kin *vs* alone	Non-kin *vs* alone	Kin *vs* alone	Non-kin *vs* alone	Kin *vs* alone	Non-kin *vs* alone
Woman (ref: MAn)	1.420* [1.025,1.967]	1.394* [1.060,1.832]	1.540* [1.106,2.144]	1.467** [1.108,1.943]	1.469* [1.052,2.053]	1.441* [1.089,1.909]
Age (in 10 years)	0.729** [0.583,0.911]	0.814* [0.674,0.982]	0.743** [0.594,0.929]	0.830 [0.686,1.004]	0.706** [0.562,0.887]	0.847 [0.698,1.028]
White (ref: non-White)	0.911 [0.522,1.590]	0.702 [0.447,1.101]	0.885 [0.507,1.545]	0.777 [0.493,1.224]	0.916 [0.521,1.611]	0.732 [0.463,1.157]
Some college (ref: high school or less)	0.847 [0.575,1.248]	1.382 [0.984,1.943]	0.880 [0.596,1.300]	1.382 [0.978,1.954]	0.826 [0.554,1.231]	1.360 [0.960,1.928]
College (ref: high school or less)	0.980 [0.664,1.447]	1.636** [1.164,2.300]	1.013 [0.689,1.489]	1.825*** [1.298,2.567]	1.011 [0.679,1.506]	1.731** [1.225,2.446]
Currently working (ref: no)	0.627* [0.438,0.897]	1.504** [1.124,2.012]	0.602** [0.423,0.857]	1.576** [1.178,2.109]	0.602** [0.420,0.864]	1.598** [1.190,2.144]
Currently married (ref: no)	3.081*** [2.278,4.166]	1.262 [0.981,1.623]	3.162*** [2.320,4.310]	1.282 [0.989,1.663]	3.248*** [2.388,4.417]	1.290 [0.999,1.667]
Depression symptoms	0.936* [0.881,0.995]	0.968 [0.920,1.018]	0.918** [0.863,0.977]	0.967 [0.918,1.018]	0.924* [0.865,0.986]	0.953 [0.904,1.005]
Functional limitations	1.058* [1.000,1.120]	1.029 [0.978,1.082]	1.077* [1.017,1.140]	1.023 [0.972,1.076]	1.066* [1.006,1.129]	1.025 [0.973,1.079]
Network size	1.064* [1.005,1.126]	1.055* [1.007,1.105]				
Network diversity	1.116 [0.872,1.427]	1.284* [1.046,1.576]				
Network density	1.340* [1.067,1.681]	1.118 [0.930,1.345]				
Gender heterogeneity			1.479 [0.587,3.726]	0.786 [0.365,1.695]		
Any racial heterogeneity			1.190 [0.838,1.688]	1.450* [1.087,1.933]		
Age heterogeneity			1.027* [1.006,1.049]	0.997 [0.979,1.015]		
Mean tie strength					0.982 [0.858,1.125]	0.895 [0.801,1.001]
Number of support functions					0.999 [0.837,1.192]	1.012 [0.874,1.172]
Morning (ref: Afternoon/evening)	0.488*** [0.404,0.590]	0.633*** [0.523,0.767]	0.489*** [0.405,0.591]	0.636*** [0.525,0.769]	0.489*** [0.404,0.591]	0.634*** [0.524,0.768]
Weekend (ref: weekday)	1.481*** [1.264,1.735]	0.690*** [0.574,0.829]	1.481*** [1.264,1.734]	0.691*** [0.574,0.830]	1.481*** [1.265,1.735]	0.690*** [0.574,0.829]
Average daily EMA completion	1.084 [0.966,1.215]	0.931 [0.832,1.042]	1.092 [0.973,1.225]	0.936 [0.836,1.048]	1.087 [0.969,1.219]	0.929 [0.830,1.040]
AIC	9194.692	9194.692	9208.327	9208.327	9215.319	9215.319
BIC	9418.526	9418.526	9432.162	9432.162	9425.986	9425.986

Notes. EMA = ecological momentary assessment. Relative risk ratios with 95% confidence intervals in brackets are reported.
"Interaction Partner Type" was coded hierarchically, prioritizing the weakest tie (e.g., other non-kin > friends/neighbors > other kin > spouse/partner) when multiple partners were present. The Base category in all models was "Being alone."
*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

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Table 4 Two-level logistic random-effects models predicting type of social activity and setting per EMA interaction, $N = 5{,}342$.

Variables	Explicit socializing (*vs* other activities)			Not at home (*vs* home)		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Woman (ref: Man)	1.396* [1.031,1.889]	1.415* [1.040,1.924]	1.493** [1.103,2.022]	1.137 [0.855,1.512]	1.171 [0.875,1.567]	1.170 [0.875,1.564]
Age (in 10 years)	0.890 [0.728,1.089]	0.909 [0.742,1.113]	0.886 [0.725,1.082]	0.806* [0.662,0.981]	0.809* [0.663,0.987]	0.826 [0.675,1.009]
White (ref: non-White)	0.880 [0.531,1.460]	0.953 [0.574,1.581]	0.870 [0.528,1.433]	1.246 [0.766,2.026]	1.230 [0.754,2.007]	1.173 [0.719,1.914]
Some college (ref: high school or less)	0.975 [0.680,1.397]	1.017 [0.707,1.464]	0.904 [0.630,1.296]	1.011 [0.715,1.428]	0.979 [0.690,1.389]	0.975 [0.686,1.386]
College (ref: high school or less)	1.022 [0.711,1.470]	1.175 [0.820,1.684]	0.988 [0.689,1.416]	1.133 [0.801,1.601]	1.126 [0.798,1.588]	1.083 [0.764,1.536]
Currently working (ref: no)	0.858 [0.621,1.185]	0.868 [0.631,1.194]	0.829 [0.604,1.140]	2.179*** [1.601,2.965]	2.201*** [1.620,2.990]	2.209*** [1.622,3.007]
Currently married (ref: no)	1.034 [0.786,1.361]	1.111 [0.840,1.469]	1.074 [0.819,1.409]	1.050 [0.806,1.367]	1.097 [0.835,1.440]	1.093 [0.838,1.426]
Depression symptoms	0.966 [0.915,1.021]	0.971 [0.919,1.025]	0.934* [0.883,0.989]	0.964 [0.914,1.017]	0.970 [0.919,1.024]	0.960 [0.908,1.015]
Functional limitations	1.056* [1.005,1.110]	1.044 [0.993,1.098]	1.063* [1.012,1.117]	0.921** [0.870,0.974]	0.922** [0.871,0.977]	0.923** [0.872,0.978]
Network size	1.059* [1.007,1.113]			0.985 [0.938,1.036]		
Network diversity	1.154 [0.927,1.437]			1.342** [1.079,1.668]		
Network density	1.118 [0.909,1.375]			1.224* [1.005,1.491]		
Gender heterogeneity		0.391* [0.175,0.877]			0.772 [0.343,1.738]	
Any racial heterogeneity		1.214 [0.884,1.666]			1.203 [0.887,1.632]	
Age heterogeneity		1.016 [0.996,1.035]			0.994 [0.976,1.013]	
Mean tie strength			0.843** [0.749,0.950]			0.932 [0.829,1.048]
Number of support functions			0.905 [0.775,1.057]			1.030 [0.884,1.200]
Morning (ref: afternoon/evening)	0.357*** [0.265,0.482]	0.359*** [0.266,0.484]	0.356*** [0.264,0.481]	0.701*** [0.597,0.823]	0.701*** [0.597,0.823]	0.701*** [0.597,0.823]
Weekend (ref: weekday)	1.498*** [1.224,1.834]	1.497*** [1.223,1.833]	1.496*** [1.222,1.831]	0.645*** [0.555,0.750]	0.646*** [0.556,0.751]	0.646*** [0.556,0.751]
Average daily EMA completion	1.061 [0.921,1.222]	1.058 [0.918,1.218]	1.054 [0.916,1.213]	0.901* [0.817,0.994]	0.898* [0.814,0.991]	0.898* [0.813,0.990]
AIC	3187.975	3190.461	3184.876	5850.249	5855.879	5854.576
BIC	3299.892	3302.378	3290.210	5962.166	5967.796	5959.910

Note. EMA = ecological momentary assessment. Odds ratios with 95% confidence intervals in brackets are reported.
*$p < .05$. **$p < .01$. ***$p < .001$.

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(Models 5 and 6). These patterns were consistent when presented as AMEs (Figure 1, Panel D).

Discussion

In the current study, we leveraged personal network data and ecological momentary assessments to examine how core networks are associated with daily social experiences in later life. We focused on three key properties of social networks–structure, heterogeneity, and strength–and evaluated their associations with momentary relational experiences that have been linked to health and well-being in prior EMA studies (Bernstein et al., 2018; Goldman & York Cornwell, 2023; Shi et al., 2024).

First, we found that at any given moment, respondents reported interacting with one person, on average, though the distribution was heavily right-skewed and zero-inflated. Respondents reported being alone more often than not, with moments spent in the company of others nearly evenly split between kin and non-kin. Explicit socializing activities occurred infrequently, and respondents were most often at home when they responded to the EMA prompt. Moreover, older adults in our study reported maintaining relatively tight-knit, affectively strong social networks with moderate bridging potential (i.e., density) and heterogeneity, consistent with the concept of core networks and prior work on social interaction preferences in later life (Carstensen, 1992; English & Carstensen, 2014).

Yet, the networks reported by our respondents are larger (about six people), on average, with substantially more variation in size (range = 2-17) relative to networks reported in EMA studies and in other population studies of older adults' networks (Cornwell et al., 2009; Goldman & York Cornwell, 2023). This likely reflects methodological differences, such as not limiting the number of named alters and using multiple name generators to elicit networks. These strategies allowed us to capture greater natural variation in network characteristics and identified significant associations between network properties consistent with bridging and momentary interactions not observable in prior studies (Goldman & York Cornwell, 2023).

Importantly, we find that structural and compositional features of social networks were consistently associated with greater real-time sociality among older adults. Our network module elicited a core, emotionally significant support network using specific name generators (e.g., discussion partners, health confidants, and leisure companions), whereas EMA prompts captured interactions with anyone present at a given moment. Notably, 30% of EMA-reported interactions (663 of 2,209) involved relationship types unlikely to appear on the network roster at all, such as coworkers, neighbors, acquaintances, or strangers, and the EMA instrument never asked whether a specific named alter was present. While we cannot rule out the overlap between the remaining EMA interaction partners and named network alters, the observed associations between network characteristics and momentary interaction reflect a substantive empirical relationship rather than a definitional artifact of overlapping measurement.

Specifically, network size was associated with greater real-time sociality, predicting a greater number of interaction partners, lower probability of being alone, and more frequent engagement in social activities. Having more core network members likely enlarges the pool of potential social partners available at any given time, enhancing opportunities for both spontaneous and planned interaction. Crucially, more network members may create resilience in real time since if one companion or supporter is unavailable at any given moment, another may be. This finding offers a potential mechanism underlying the well-documented association between network size, reduced isolation and loneliness, and lower morbidity and mortality (Czaja et al., 2021; Domènech-Abella et al., 2021; Holt-Lunstad, 2024; Holt-Lunstad et al., 2010). Namely, rather than operating solely through perceptual or social psychological pathways, our findings suggest that older adults with larger networks may have expanded opportunities for social participation in real time.

The most theoretically significant implication from this research is that different network properties may be linked to distinct partner types and patterns of momentary sociality, rather than uniformly corresponding to greater social contact of any kind. Though role diversity and network density are theoretically linked to opposing structural mechanisms (i.e., bridging and bonding, respectively), both were associated with greater sociality (i.e., more social interaction partners, less aloneness, and more time outside the home). Yet, they produced qualitatively distinct patterns of momentary exposure. Specifically, role diversity was associated with disproportionate exposure to interactions outside the family, while density was associated with greater within-family interactions. An implication of these results is that both role diversity and density, which theoretically correspond to bridging and bonding, respectively, might afford older adults access to distinct social opportunities–one via exposure to novelty and nonredundant opportunities, and the other via cohesive, reinforcing, and habitual interactions.

Sociodemographic heterogeneity showed a parallel pattern of specificity. Age heterogeneity, consistent with membership in intergenerational networks (e.g., exposure to grandchildren), was associated with a greater likelihood of kin-centered contact. Conversely, racial heterogeneity was associated with greater exposure to non-kin interactions, such as those occurring at work, in the neighborhood, or through structured social activities (Blau, 1977; Ellwardt et al., 2015; McPherson et al., 2001). Indeed, supplementary analyses indicated that this association of racial heterogeneity with non-kin interaction was attenuated in models that jointly accounted for network size and diversity, suggesting that it may partly reflect shared variance with structural features that are consistent with bridging mechanisms. Together, these findings imply that network heterogeneity does not simply expand the total volume of momentary social contact. Instead, distinct compositional features of personal networks may correspond to different kinds of interactional opportunities for older adults, resulting in divergent everyday social experiences. However, while the racial heterogeneity finding is directionally consistent with this pattern, it should be interpreted with caution given its attenuation under joint estimation.

A further, and in some ways counterintuitive, contribution of this study is that strong, supportive ties theoretically consistent with bonding networks did not translate into greater momentary social exposure. In fact, respondents embedded in networks with *weaker* average tie strength were more likely to engage in explicit socializing activities, such as visiting a neighbor or having coffee with a friend, and tie strength and supportiveness were not significantly associated with the number or type of

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interaction partners. One possible explanation, though speculative, is that embeddedness in affectively close networks reflects social needs already met through routine or co-residential contact, reducing the motivation to seek out additional explicit socialization. However, these associations persisted after adjusting for marital status, suggesting they may reflect broader network context rather than simply co-residence. It is also possible that weak-tie networks function similarly to bridging networks more generally, providing access to a broader set of potential interaction partners through group and community activities. Regardless, this finding implies that the relationship between network strength and everyday social experience is not a simple, mechanical one. Closer ties are not associated with more momentary sociality in a straightforward way, and in some respects may substitute for it (Cornwell, 2009; Putnam, 2000).

Our results have implications for the growing literature on time diary research, suggesting that U.S. adults are spending increasing amounts of time alone and at home (Atalay, 2024; Sharkey, 2024). Sharkey's (2024) research suggests that time spent at home is associated with less time with friends, and more time alone has raised concerns about growing social isolation, especially in the home environment. Our findings suggest that this trend may depend on the structure and composition of people's personal social networks. Namely, respondents embedded in denser and kin-centered networks in our study were more likely to interact with family members while at home. This is consistent with Peng's (2025) finding that the home is the largest source of daily social contact for those who cohabit with family and the greatest source of isolation for those who live alone. Conversely, respondents in our study with a greater diversity of social roles in their networks were more likely to leave the home to interact with non-kin contacts, suggesting their momentary social lives may be organized around settings beyond the household altogether. Taken together, these patterns imply that the aggregate rise in time spent home and alone documented in the time-use literature may mask considerable heterogeneity across older adults that is patterned, in part, by the structure of their personal networks. Rather than a uniform experience, time at home appears to function as socially generative for some older adults and socially isolating for others, depending on the structure and composition of their networks.

The divergent pathways identified in our study carry distinct implications for older adults' health and well-being, suggesting that network-associated momentary social contact may not be uniformly beneficial. Instead, it may confer different kinds of health-promoting resources depending on whether the network exhibits characteristics theoretically linked to bridging or bonding (Hamilton et al., 2026). Momentary interactions arising from network features (e.g., role diversity and racial heterogeneity) may expose older adults to non-kin ties in more diverse social circles at work, in the neighborhood, and through structured community activities. Though speculative, this kind of exposure may be especially valuable for feelings of community integration and access to novel information, resources, and cognitive stimulation that are beneficial for reduced loneliness and better psychological and cognitive health (Blau, 1977; Ellwardt et al., 2015; McPherson et al., 2001; Perry et al., 2022; Ramos et al., 2024). In contrast, momentary interactions rooted in network density and age heterogeneity associated with closure more often channel older adults toward kin-centered contact, likely including intergenerational exchanges with children and grandchildren. Though beyond the scope of our data, existing research suggests these interactions may be less about novelty and more about emotional security, identity affirmation (e.g., through roles such as caregiver or grandparent), and instrumental support (e.g., help with technology, transportation, or physical tasks) (Coleman, 1988; Cornwell, 2009; Drury et al., 2017; Lin 2002; Perry et al., 2022; Whear et al., 2023; Zhong et al., 2020). Taken together, these findings are consistent with the theory that distinct network features do not simply produce more social contact interchangeably but instead channel older adults toward qualitatively different social resources, with potentially unique implications for health and well-being.

Limitations

This study has several limitations. First, our sample is representative of the state of Indiana, but more homogenous with respect to race and ethnicity and skews toward women than the United States as a whole. The sample is also relatively young for a study of later-life social engagement (mean age about 67 years), and roughly half remained employed. Social interaction patterns generated by diverse networks may therefore partly reflect work-related contexts that do not extend to the oldest old or the fully retired. Similarly, findings may not be generalizable to more populous or racially and ethnically diverse populations. In particular, results on racial heterogeneity should be interpreted with caution. Because our sample is predominantly White (92%), only 23% of networks contain any racial heterogeneity, limiting both the variation available to detect associations and the generalizability of these findings to more racially diverse populations. A binary measure of this kind may also simply be a proxy for other structural factors rather than an indicator of racial diversity specifically. Nonetheless, future research with more racially diverse samples and more granular measures of racial composition is needed to clarify these relationships.

Second, selection into the EMA module is a potential source of bias. Participants in our sample who agreed to the EMA module are younger, more likely to hold a college degree, and report more frequent computer use than those who did not. This pattern means that our findings underrepresent older, less resourced, and less technologically engaged older adults. Although results adjusting for daily computer use yielded results entirely consistent with estimates without such adjustment, selection on unmeasured demographics, health outcomes, or aspects of digital literacy cannot be ruled out. We call for future research to extend EMA designs to less technologically engaged populations, such as the oldest old and other groups affected by the digital divide.

Third, although EMAs were administered following the in-person interviews, these data are essentially cross-sectional. As such, we cannot establish causality. In fact, it is likely the relationship between social network characteristics and momentary social interactions is bidirectional, such that repeated social interactions, considered in aggregate, constitute and reinforce personal social networks, while networks in turn constrain and enable interactions. This bidirectionality is consistent with Feld's theory of foci activity, which states that relationships and social interactions form and are maintained through repeated

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social contact centered around shared foci, or social, institutional, and spatial contexts such as workplaces, neighborhoods, and families (Feld, 1981). Additional longitudinal research containing personal network and EMA data over a much longer timespan is needed to disentangle the dynamic and likely reciprocal relationship between personal networks and the everyday interactions they enable.

Despite these limitations, our study has notable strengths, including high-dimensional social network data combined with rich EMAs. As such, our analysis offers one of the first empirical examinations of how personal social networks are linked to realized daily exposures. We find patterns supporting the theory that social networks function as enduring relational structures that can be activated in daily life, shaping not simply how often older adults interact, but with whom, in what settings, and toward what kinds of social resources. Critically, this influence is not uniform. Rather, network features associated with bridging and bonding may channel older adults toward different partner types and correspondingly distinct social resources. That is, expanded exposure, novelty, and community integration on the one hand, and emotional security, identity affirmation, and kinship support on the other. This pattern is consistent with the theory that social networks do not simply produce more or less social contact but instead structure the qualitative character of everyday social life in ways that likely carry distinct implications for psychological, social, and physical health.

Supplementary material

Supplementary material is available at *The Journals of Gerontology, Series B: Psychological Sciences and Social Sciences* online.

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Conflicts of interest

A. R. Roth is the organizer of the supplement in which this article is published but was not involved in the manuscript's review process or decision to accept it for publication. Other authors have no conflicts to declare.

Data availability

This study was not preregistered. SECHURA data will be made available upon request at a future date.

Ethics approval

The SECHURA study was approved by the Institutional Review Board at Indiana University (IRB-IUB-16000) and exempted by the Institutional Review Board at Oklahoma State University (IRB-22-351).

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