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Network recall among older adults with cognitive impairments

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Abstract

Although it is widely accepted that personal networks influence health and illness, network recall remains a major concern. This concern is heightened when studying a population that is vulnerable to cognitive decline. Given these issues, we use data from the Social Network in Alzheimer Disease project to explore similarities and discrepancies between the network perceptions of focal participants and study partners. By leveraging data on a sample of older adults with normal cognition, mild cognitive impairment, and early stage dementia, we explore how cognitive impairment influences older adults' perceptions of their personal networks. We find that the average individual is more likely to omit weaker, peripheral ties from their self-reported networks than stronger, central ties. Despite observing only moderate levels of focal-partner corroboration across our sample, we find minimal evidence of perceptual differences across diagnostic groups. We offer two broad conclusions. First, self-reported network data, though imperfect, offer a reasonable account of the core people in one's life. Second, our findings assuage concerns that cognitively impaired older adults have skewed perceptions of their personal networks.

Keywords

Personal networks; network recall; cognitive impairment; older adults

INTRODUCTION

A long line of inquiry demonstrates that social relationships—and the networks in which they are embedded—play a central role in health and illness (Pescosolido 1992; Roth 2020; Smith and Christakis 2008; Umberson and Montez 2010). Social networks protect individuals from a range of adverse outcomes, including but not limited to mortality, psychological distress, and cognitive decline (Berkman and Syme 1979; Ellwardt, Van Tilburg, and Aartsen 2015; Song 2011). In service of developing preventative interventions,

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substantial research has focused on identifying the pathways linking social networks and health. Yet, these studies are grounded in the assumption that people provide accurate accounts of their personal networks—an assumption that has been widely scrutinized (Bell, Belli-McQueen, and Haider 2007; Brewer 2000; Marin 2004; Yousefi-Nooraie et al. 2019).

As early as the 1970s and 1980s, methodologists questioned how well people recall social interactions (Bahrick, Bahrick, & Wittlinger, 1975; Bernard & Killworth, 1977; Hammer, 1984). Initial findings that compared recall data against observed social interactions suggested that self-reports were poor proxies for actual patterns of interactions. These findings led Bernard, Killworth, and Sailer (1981) to conclude that “people do not know, with any acceptable accuracy, to whom they talk over any given period of time” (p. 15). Subsequent researchers, however, conducted nuanced analyses that challenged these earlier claims (Freeman, Romney, and Freeman 1987; Kashy and Kenny 1990; Romney and Weller 1984).

Although network recall remains an issue in the general population, it becomes increasingly concerning when studying a population that is vulnerable to cognitive decline, severe mental illness, or similar conditions. Indeed, a burgeoning literature addresses the relationship between social networks and cognitive function among older adults (Ellwardt et al. 2015; Fratiglioni et al. 2000; Litwin and Stoeckel 2016). The predominant conclusion is that higher levels of engagement in larger personal networks slow the onset of cognitive decline in later life (Kelly et al. 2017). However, a perennial concern among these types of studies is the potentially systematic underreporting of alters among those with cognitive impairment. In other words, older adults who perform worse on cognitive assessments may not actually have smaller personal networks than their higher performing counterparts. Rather, they may be more likely to omit certain alters *because* of their cognitive impairment. Therefore, it is crucial to assess how cognitively impaired older adults perceive their personal networks in comparison to cognitively normal older adults. Identifying the types of alters who are omitted is also important given that certain kinds of relationships or interactions may be more influential than others in preventing cognitive decline (Perry, Risacher, Tallman, Apostolova, & Saykin, 2017).

A variety of approaches have been employed to address the issue of network recall. Whereas early research relied on observational data to assess reports of social interactions (Bernard and Killworth 1977; Freeman et al. 1987; Romney and Weller 1984), subsequent studies compared network reports from multiple parties to determine the level of agreement between different perspectives (adams and Moody 2007; Antonucci and Israel 1986; Crotty and Kulys 1985; Stansfeld and Marmot 1992; Stein, Rappaport, and Seidman 1995; White and Watkins 2000). Yet, nearly all of these latter studies focused solely the degree of overlap between informant accounts only to ignore the sources of discrepancy. We contend that these discrepancies are themselves worthy of investigation (Hammer 1984). As noted by Pescosolido and Wright (2004), what was previously considered an inherent reporting problem can be used to provide unique insights into “how social ties occur, where reports are mismatched, and what factors are associated with discrepancies in multiple perspective network data” (p. 1796).

In the present paper, we analyze data from the Social Network in Alzheimer Disease (SNAD) project to address the above issues. SNAD contains data on a sample of older adults in three clinically diagnosed groups: cognitively normal, mild cognitive impairment, and early stage dementia. These older adults are members of a larger NIH-funded cohort study at the Indiana Alzheimer Disease Center (IADC). In addition to undergoing a series of clinical assessments, focal participants were administered a social network protocol during their annual study visit to the IADC. Each participant was accompanied by a study partner who served as a secondary informant. In order to address concerns over network recall, study partners provided their accounts of the focal participants' personal networks. Following Pescosolido and Wright (2004), we adopt a 'view from two worlds' approach in which we consider both network-level similarities and alter-level discrepancies between each party's report. Whereas the former quantifies the extent to which reports overlap, the latter tells us how they are different. We address the following research questions: (1) How well do participants' and partners' network reports corroborate one another? (2) Which type of alters are responsible for discrepancies between reports? (3) Does the degree of corroboration vary across clinical diagnoses?

BACKGROUND

Network Recall

Personal network data collection commonly relies on name generators to elicit a set of alters. Name generators delineate networks by asking informants to list alters who fit a specific criterion (Perry, Pescosolido, and Borgatti 2018). The ability to recall each alter depends on the nature of the name generator. Before informants begin to provide names, they must first interpret what is being asked of them (Bailey and Marsden 1999). This is more straightforward in some case than others. For example, most people agree on what constitutes a family member, but there is significant variation in how individuals interpret a confidante (Bearman and Parigi 2004). Once informants interpret the name generating prompt, they must rely on their memory to decide who to name. This introduces additional sources of bias, as certain relationships are easier to recall than others. Nearly everyone remembers their direct family members, but many people struggle to recall those with whom they discussed important matters in the past six months (Marin 2004). Consequently, one of the most fundamental issues in the network literature is whether people can accurately identify alters within their personal networks (Brewer 2000; Hammer 1984; Marsden 1990). Addressing this concern is crucial because inaccurate network data interferes with the ability to use aggregated network measures to predict individual-level outcomes (Marin 2004; Perry et al. 2018). It also has practical consequences in that people with inaccurate perceptions of who is in their social network are less likely to derive potential benefits from these networks (Brands 2013).

Classic studies by Bernard, Killworth, and Sailer (Bernard and Killworth 1977; Bernard, Killworth, and Sailer 1979; Bernard et al. 1981; Bernard, Killworth, and Sailer 1982) first problematized the validity of self-reported network data by comparing participants' recall of social interactions with observational data on social interactions within a number of bounded settings. They concluded that the average person could not accurately provide an account of whom was in their social network. Others responded by conducting empirical studies designed to contextualize social interactions within a broader social structure (Freeman et al. 1987; Kashy and Kenny 1990; Romney and Weller 1984). These latter studies found that although individuals could not accurately recall who was involved in specific social interactions (e.g., attendance at a department colloquium), they tended to identify recurring patterns of social interactions (e.g., typical attendance at colloquium series). Drawing on insights from cognitive psychology, Freeman et al. (1987) concluded that participants relied on "mental structures that reflect the regularities of their experiences" (p. 322).

Building on Freeman et al. (1987), numerous theoretical and empirical studies have concluded that informants employ cognitive schemata to help them depict the general structure of their social networks rather than recalling alters at random (Brashears 2013; Brewer 1995; Marsden 2005). Network properties such as density affects the ability to accurately recall specific members of a network. For instance, Brashears (2013) found that experiment participants were more accurate in identifying ties between people clustered within closed triads as opposed to those situated within lone dyads. Marin (2004) found that survey respondents were more likely to list strong, centralized ties in response to the standard important matters name generator. Network size also matters for recall as larger networks are more cognitively difficult to store in memory (Brewer and Webster 2000). Based on these insights, we formulate our first hypothesis:

H1: *Focal participants reporting smaller, denser personal networks will have higher degrees of partner agreement compared to those reporting larger, more loosely-connected personal networks*.

Who is Omitted?

Hammer (1984) previously noted that network studies are "seriously limited by the absence of information on the accuracy of respondents' reports, and even more seriously by the absence of information on the people the respondents do not mention" (pp. 342–343). The omission of specific alters may prove consequential across a range of egocentric network studies. For example, Granovetter (1973) famously found that weak ties were the most influential in helping people identify jobs opportunities. Goldman and Cornwell (2015), meanwhile, found that older adults who served as a bridge between at least two alters were more likely to use alternative medicine compared to those who reported no bridging potential within their personal networks. In both instances, the presence of a single peripheral alter had meaningful consequences. Had the subjects of these studies failed to report ties to these alters, the researchers would have been unable to identify the network processes leading to these outcomes. Given that individuals often omit certain alters within their personal networks (Brewer 2000), it is instructive to explore exactly which types of alters are not mentioned.

Research suggests that individuals are likely to omit those who occupy the fringes of a social network (Brewer 2000; Freeman et al. 1987; Marsden 1990). This occurs because of the ways in which social networks are cognitively encoded in the human mind (Brashears 2013). From an egocentric perspective, peripheral ties—alters who are less central in the network—are more likely to be weaker ties (i.e., ties marked by emotional distance and infrequency of contact) and therefore more likely not to be at the forefront of ego's mind (Marin 2004). These considerations inform our second hypothesis:

H2: *Peripheral ties and weak ties will be more likely to be omitted compared to central ties and strong ties*.

Social roles also influence network recall (Perry and Pescosolido 2010). Given their propensity to fulfill emotionally strong social roles, people are less likely to forget to name family members than non-family members, especially in response to name generators that elicit close personal relationships (Fischer and Offer 2020). Family members also tend to occupy dense clusters which make them cognitively easier to remember (Brashears 2013; Marsden 1987). Non-kin, meanwhile, occupy heterogeneous social roles. Any given list of non-kin alters may include friends, co-workers, religious leaders, medical professionals, or mere acquaintances. Even friends—arguably the closest type of non-kin relationship—are forgotten at remarkably high rates (Brewer and Webster 2000). Moreover, the diversity of functions that non-kin provide decreases their overall likelihood of being listed in response to any given name generator. With this in mind, we formulate our third hypothesis:

H3: *Non-kin will be more likely to be omitted compared to kin*.

Differences Across Cognitive Impairments

To date the majority of the network recall literature focuses on whether the average individual provides accurate network data rather than addressing systematic variations across individuals. Although the former is an important methodological concern, the latter presents an intriguing substantive question: Do certain groups perceive their personal networks differently than others? Given the central role of cognitive processes in network recall, we direct special attention towards older adults with varying levels of cognitive impairments. There are two potential reasons to expect network recall to differ across clinical cognitive diagnoses: memory problems and network heterogeneity.

Despite disagreement over the accuracy of self-reported data, there is broad consensus that network recall operates through cognitive processes (Bernard et al. 1984; Brashears 2013; Freeman et al. 1987; Stiller and Dunbar 2007). In other words, the processes through which individuals store and retrieve information are responsible for the way they understand their position with a social network (Brands 2013). The ability to provide accurate self-reported data, therefore, likely varies according to cognitive function (Farias, Mungas, and Jagust 2005). Because dementia is frequently characterized by memory loss, we may expect older adults with cognitive impairments to be more likely to forget to name certain alters in their personal networks than cognitively normal older adults. Based on these insights, we generate our fourth hypothesis:

H4a: *Discrepancies between focal-partner perceptions will be larger for focal participants with more severe cognitive impairments*.

Memory issues aside, individuals maintain different types of personal networks based on a combination of factors, including their current health conditions. Extensive research suggests that people in poor physical and mental health tend to occupy more restricted personal networks than those in good health (Cornwell 2009; Haas, Schaefer, and Kornienko 2010; Li and Zhang 2015; Perry and Pescosolido 2015). A similar trend emerges among dementia patients as older adults with cognitive impairments report smaller and denser personal networks than their cognitively normal counterparts (Perry et al. 2017). If these self-reports are an accurate representation of their social interactions, we might instead expect older adults with cognitive impairments to have an easier time recalling alters by virtue of the fact they have fewer alters to name. In light of these considerations, we offer an alternative hypothesis:

H4b: *Discrepancies between focal-partner perceptions will be smaller for focal participants with more severe cognitive impairments*.

METHODS

Sample

Data come from the Social Networks in Alzheimer Disease (SNAD) project. SNAD participants are members of an NIH-funded cohort study at the Indiana Alzheimer Disease Center (IADC). The IADC recruits older adults with varying levels of cognitive impairment as well as a control group of cognitively normal older adults. The goal of the IADC is to clinically characterize and track older adults who either have or are at risk of developing Alzheimer's disease or related dementia. To qualify for the enrollment at the IADC, all participants were required to enroll with a study partner who would serve as a secondary informant. Focal participants were administered a battery of clinical assessments and neuroimaging procedures, all of which inform a cognitive diagnosis. From March 2015 to May 2019, all eligible IADC participants were approach to voluntarily complete the SNAD network protocol. During their study visit to the IADC, focal participants were administered a baseline social network protocol via face-to-face interview. Study partners were separately administered the same network protocol to determine their perceptions of the focal participants' personal networks. The analytic sample size for the current study is 140 after excluding participants with missing network data from their study partner (n=148), severe cognitive impairments (n=15), and participants under the age of 45 (n=13).[1]

Measures

Personal Network Data—Name generators were used to elicit alters who were activated in the past six months for discussions about important matters and health matters using an expanded version of the PhenX Social Network Battery (SNB) tailored to the case of dementia (PhenX Toolkit 1991). These two name generators were used to elicit a core network (Marsden 2005; Perry and Pescosolido 2010). No limit was placed on the number of alters that could be named in response to either generator. The name generators occurred at the beginning of the interview to mitigate any potential ordering effects (Pustejovsky and Spillane 2009; Yousefi-Nooraie et al. 2019).

[1]As a marker of severe cognitive impairment, we excluded participants who scored below 10 on the Montreal Cognitive Assessment (Nasreddine et al. 2005). We also excluded participants under the age of 45 because these individuals were either not old enough to experience age-related cognitive decline or they suffer from early-onset dementia, which is a unique type of dementia that is beyond the scope of the present study.

After the list of names was provided, a series of name interpreters was used to gather further information on each alter. These name interpreters asked about *frequency of contact* ('often,' 'occasionally,' 'hardly ever'), *emotional closeness* ('very close,' 'sort of close,' 'not very close'), and *relationship type* ('spouse/partner,' 'parent,' 'child,' 'friend,' 'neighbor,' etc.). Another series of questions asked about alter-alter relationships. These questions were used to compute structural measures of the network. *Density* is a network-level variable that was calculated as the proportion of alters who were 'sort of close' or 'very close' with each other. *Alter centrality* is an alter-level variable that was calculated as the percent of other alters with whom each alter shared a tie.

Network Perception

There are multiple ways to assess network perception at the egocentric level (Freeman et al. 1987; Marin 2004; Marsden 1990; Pescosolido and Wright 2004). Because we have data from two sources (focal participant and study partner), we rely on two related measures that assess similarity of network perceptions: *corroboration* and *overlap*. The first measure is calculated using the following equation:

$$\text{Corroboration} = \frac{\mathrm{n_c}}{\mathrm{n_f} + \mathrm{n_p} + \mathrm{n_c}}$$

where n_c equals the number of alters named both by the focal participant and study partner (i.e., corroborated alters), n_f equals the number of alters named solely by the focal participant, and n_p equals the number of alters named solely by the study partner.[2] The corroboration value equals the number of corroborated alters divided by the total number of non-redundant alters pooled across the two reports. Possible values range from 0.0 to 1.0 with higher values signaling higher corroboration.

Whereas the corroboration measure directly adjusts for the total number of alters named by each party, the overlap measure favors the focal participant's report. This measure is the percentage of focal-named alters that partners also named in their reports. Accordingly, it is calculated using the following equation:

$$\text{Overlap} = \frac{\mathrm{n_c}}{\mathrm{n_f}} \times 100$$

where n_f equals the total number of alters named by the focal participant and n_c equals the number of alters named by both the focal participant and study partner. The quotient is multiplied by 100 to convert the measure into a percentage. Figure 1 shows an example of these two measures using a hypothetical focal-partner case.

Although the corroboration and overlap measures are intended to assess the same concept (i.e., network perceptions), they deviate in important ways. The corroboration measure treats each party's perception of the network as equally valid and penalizes for each unique alter

[2]This corroboration measure is adapted from Perry and Pescosolido's (2012) network turnover measure, which assesses instability of alters within a network over time.

named by focal and partner. The overlap measure also accounts for each party's perspective, but privileges the focal participant's perception as a baseline comparison. By these standards, partners who name more alters have better chances of scoring higher on the overlap measure, regardless of whether some of these alters were not named by the focal participant. Because there is no standard method for comparing network perceptions, we analyze both outcomes in parallel.[3]

Alter Discrepancies

Because we are also interested in identifying where perceptual discrepancies exist, we created a binary measure that indicated if a focal-named alter was omitted by the study partner (0 = not omitted, 1 = omitted). This is illustrated in Figure 1, in which 'Daughter,' 'Son,' and 'Spouse' were all named by the focal as well as the partner whereas 'Eric' and 'Jesse' were named by the focal but omitted by the partner. To assess the perceptions of the study partner, we created a separate measure that indicates if a partner-named alter was omitted by the focal participant. By this measure, 'Austin' and 'Phil' were named by the partner but omitted by the focal in Figure 1.

Attribute Data

As part of the IADC protocol, all focal participants underwent numerous clinical assessments and neuroimaging procedures. These assessments were used to clinically diagnose participants into one of the three following categories: *cognitively normal* (CN), *mild cognitive impairment* (MCI), or *early-stage dementia*. We control for the following focal participant attributes: *sex* (male = 0, female = 1), *age* (years), *education* (years completed), and *co-residence* (0 = focal and partner live apart, 1 = focal and partner live together).

Analytic Strategy

The analysis proceeds in two steps. First, we use linear regression models to estimate the network-level outcomes (i.e., corroboration and overlap) using aggregate measures of alter attributes (e.g., percent kin, percent close) as well as ego attributes (e.g., sex, age, co-residence) as predictors. These models test H1 and H4, which posit that network attributes and clinical diagnoses will be independently associated with network perceptions. Second, we use logistic regression models to estimate the odds of an alter being omitted during recall. These models use alter attributes (e.g., kin, emotional closeness) as well as ego attributes as predictors. Aggregate network-level attributes are also included to account for a contextual effect when their corresponding alter attributes are used (e.g., alter closeness + percent close) (Perry et al. 2018). These models test H2 and H3, which posit that certain types of alters will be more likely to be omitted than others. Although multi-level models are advisable when performing alter-level analysis with egocentric network data (Perry et al. 2018), we found no evidence of intraclass correlation. Therefore, we proceed using logistic

[3]Although the corroboration and overlap variables are significantly correlated ($r = 0.80$, $p < 0.001$), a two-way scatterplot shows clear signs of heteroscedasticity (see Supplementary Figure 1). Whereas network corroboration is closely correlated with overlap at lower values, the two variables becomes increasingly orthogonal as the values reach the upper limits of the overlap variable. This is because the overlap measure does not penalize partners who name many alters whereas the corroboration measure does.

regression models with robust standard errors to account for alters being clustered within networks. All analyses were performed using Stata 16 StataCorp 2019).

RESULTS

Network-level Analysis

Table 1 provides descriptive statistics at the network level. The mean corroboration value for the sample is 0.47. In other words, less than half of the alters within each network were matched from reports of focal participants or study partners. The average study partner, meanwhile, correctly matched 65 percent of alters named by the focal participant. As expected, personal networks were more restricted for those with worse clinical diagnoses. Cognitively normal older adults reported having the largest networks ($\bar{x} = 5.28$, range: 2–16) followed by those with MCI ($\bar{x} = 4.31$, range: 2–8) and dementia ($\bar{x} = 4.38$, range: 1–11). Focal participants' reports of density ($F = 3.93$, $p < 0.05$) and percent kin ($F = 3.50$, $p < 0.05$) also exhibited significant differences across diagnostic groups. Cognitively normal older adults' networks were the least dense ($\bar{x} = 0.64$) and consisted of the lowest proportions of kin (61.15 percent).

Tables 2 and 3 show results from linear regression models predicting network corroboration and network overlap, respectively. The results from these tables indicate a negative relationship between network size and network perception. In other words, perceptual similarities are higher when the focal participant reports fewer alters. Model 2 in Table 3 shows that for every additional focal-named alter, the percent of focal-named alters that were also named by the study partner decreases by 4.6 percent. Figure 2 offers a visual account of this relationship. Density, kin composition, and closeness are all positively related to corroboration and overlap. Frequency of contact with alters, however, is only significantly related with overlap (Table 3, Model 6, $\beta = 2.53$, $SE = 0.86$). Collectively, these findings lend support to H1, which states that focal participants reporting smaller, denser networks will have higher degrees of corroboration compared to those reporting larger, more loosely-connected personal networks.

As seen across models in Tables 2 and 3, cognitive impairment is not significantly associated with network perception. These findings fail to support either H4a or H4b, which both predicted significant differences across diagnostic groups but in opposite directions. By all accounts, older adults with clinically diagnosed cognitive impairments did not systematically differ in their perceptions of their networks compared to their cognitively normal counterparts.

Alter-level Analysis

Table 4 provides descriptive statistics at the alter-level as reported by the focal participant and study partner. The top half of the table shows alter attributes from the focal person's perspective. Nearly 40 percent of these alters were omitted by the study partner. Meanwhile, 60 percent were immediate family members or extended kin. A majority were considered emotionally 'very close' to the focal participant and interacted with them on a frequent basis. Due to the strong nature of these ties, the average focal-named alter shared direct ties with approximately 59 percent of the other alters within the network. The bottom half of Table 4 presents the alter attributes from the study partner's perceptive. On aggregate, these partner-named alters are similar to the focal-named alters.

Focal Perspective

Table 5 presents the results from logistic regression models predicting study partner's omission of a focal-reported alter. Similar to the models predicting network-level perceptions, none of the ego attributes—including cognitive diagnosis—were significantly associated with the outcome. Interestingly, there was no significant association between co-residence and alter omission. In other words, study partners who lived with the focal participants were neither more nor less likely to identify focal-named alters compared to partners who did not live with focal participants.

Model 2 shows that alters who are very close to the focal participant had significantly lower odds of being omitted by the study partner compared to alters who are not very close to the focal (OR = 0.18, $p < 0.001$). Model 3 shows a similar trend for frequency of contact. Alters who see or talk to the focal participant often had significantly lower odds of being omitted by the study partner compared to alters who see or talk to the focal on a less frequent basis (OR = 0.15, $p < 0.001$). Whereas these models indicate that relationship salience is closely associated with alter omission, Model 4 assesses the association between alter centrality within the network and the odds of being omitted from the study partner's self-report. As hypothesized, central alters had lower odds of being omitted than peripheral alters (OR = 0.98, $p < 0.001$). Figure 3, which plots the predicted probabilities, shows that focal-named alters who are not connected to any other alters in the network had a 68 percent probability of being omitted. Probability of omission decreases steadily as centrality increases to the point where the most central alters (i.e., those connected to all other alters) had a 20 percent probability of being omitted from the partner's self-report. Collectively, the findings from Models 2–4 support H2, which states that peripheral ties and weak ties will be more likely to be omitted than central ties and strong ties.

Model 5 turns attention to the alter-focal relationship. Spouses (OR = 0.03, $p < 0.001$), children (OR = 0.14, $p < 0.001$), and siblings (OR = 0.32, $p < 0.001$) had significantly lower odds of being omitted compared to non-kin. Figure 4 visualizes these associations by plotting the differences in predicted probabilities of alter omission for each relationship type compared to non- kin. These findings broadly support H3, which states that non-kin ties will be more likely to be missing from focal participant's accounts compared to kin ties.

Finally, we ran a series of interaction models to determine whether any of the above associations differed by diagnostic groups. There were no significant findings across these models (results not shown). Although the findings from Table 5 indicate that alter attributes are important predictors of perceptual discrepancies, these associations do not appear to be compounded by cognitive impairment.

Partner Perspective

Table 6 presents the results from logistic regression models predicting omission from the study partner's perspective. These models assess the odds that a partner-reported alter is omitted by the focal participant. On the whole, the results from these models closely mirror the results from the models from Table 5 that rely on the focal participant's perspective. The only notable difference is in Model 5, which assesses alter-focal relationship. Spouses still had significantly lower odds of being omitted compared to non-kin (OR = 0.14, $p < 0.001$), but children and siblings were no longer significantly different than non-kin. Interestingly, partner-reported alters who were extended kin had over three times greater odds of being omitted by the focal compared to non-kin (OR = 3.30, $p < 0.01$).

DISCUSSION

Network recall has long been a methodological concern for network analysts. Although a significant body of research suggests that informants rely on cognitive schemata to recall social networks (Brashears 2013; Freeman et al. 1987; Stiller and Dunbar 2007), no existing study considers how cognitive impairments may influence informants' perceptions of their own personal networks. By eliciting self-reported network data from a sample of older adults with varying levels of cognitive impairments as well as reports from their study partners, the SNAD data provide a rare opportunity to compare two independent perceptions of the same egocentric network. In the present study, we leveraged these data to adopt a 'view from two worlds' approach in which we considered the network-level similarities between reports as well as the sources of discrepancies at the alter-level.

Consistent with previous studies (adams and Moody 2007; Antonucci and Israel 1986; Pescosolido and Wright 2004; Stein et al. 1995), we found moderate to high levels of agreement between focal participants and study partners in their perceptions of focal participants' important matters and health matters networks. On average, study partners were able to freely recall 65% of alters who were originally named by the focal participant. As anticipated by H1, focal participants with smaller and denser networks exhibited higher levels of agreement with their study partners in terms of the specific alters who occupied their personal networks. Networks with larger proportions of kin and emotionally close alters also exhibited higher levels of agreement between parties compared to networks with fewer kin and more emotionally distant alters.

Whereas the network-level analyses quantified the extent to which perceptions aligned, the alter-level analyses identified specifically where the discrepancies occurred. Again consistent with previous studies (Bell et al. 2007; Brewer 2000; Marin 2004), we found that peripheral ties and weak ties served as primary sources of perceptual discrepancies. More specifically, emotional closeness, frequency of contact, and alter centrality were all significant predictors of whether an alter would be omitted from the opposing party's report. Relationship status between focal participant and alter was also a strong predictor of omission as immediate family members tended to be the least likely to be omitted.

Together these network-level and alter-level findings have important implications for egocentric network studies that rely on self-reported data. First, our findings suggest that self-reported network data, though imperfect, offer a reasonable account of the core people in one's life. Second, and more importantly, we found no evidence that focal participants with clinically diagnosed cognitive impairments had skewed perceptions of their personal networks. Indeed, cognitively impaired older adults showed no differences in their ability to corroborate accounts of their personal networks compared to their cognitively normal peers. Not only were there no significant differences at the network-level—indicating that older adults had similar views of their social lives regardless of their cognitive impairments—there were also no significant differences at the alter-level. In other words, cognitively impaired older adults were not omitting alters from their reports in any systematically different manner than cognitively normal older adults. This latter null finding is especially important because certain types of relationships have been shown to exhibit greater influence on personal health and well-being than others (Ellwardt et al. 2015; Goldman 2016; Lee and Szinovacz 2016). Therefore, from a methodological standpoint it is encouraging to learn that older adults with mild cognitive impairments and early stage dementia are no more likely to omit specific alters during network recall compared to cognitively normal older adults.

Limitations

This study has two important limitations. First, we do not know the reasons why focal participants and study partners omitted alters during network recall. When dealing with a cognitively impaired sample, one obvious explanation is that participants forgot to name certain alters. But memory is not the only reason that alters may be omitted. Subjective interpretations of different name generators can lead to the inclusion of certain alters and the omission of others (Bearman and Parigi 2004; Fischer and Offer 2020). In the present study, it is possible that focal participants omitted partner-reported alters not because they forgot them, but because they did not feel as though they discussed important matters and/or health matters with those alters. Parsing these distinctions would require us to show focal participants their partners' network rosters and asking them to explain why they did not include each alter in their original account. Due to time constraints, we did not engage in this exercise. Second, our sample only included older adults with either mild cognitive impairment or early-stage dementia (as well as a cognitively normal control group). Therefore, any conclusions reached in this study about the role of cognitive impairment in network recall cannot speak to individuals with severe impairments, including those in the advanced stages of dementia.

CONCLUSION

This study contributes to the literature on network recall by analyzing the similarities and discrepancies between multiple network perspectives. Beyond identifying the associations between network attributes and network perception, we focused on cognitive impairment as a potential contributor to recall error. Although researchers agree that individuals draw on cognitive schemata to recall their social networks, we found no evidence that cognitively impaired individuals had skewed perceptions of their personal networks relative to those who are cognitively normal. This has important implications for future work that uses self-reported network data to assess cognitive decline and other health issues among an older population.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Highlights

- Compares network perceptions between older adults and their study partners
- Identifies network-level similarities and alter-level discrepancies between reports
- Assess whether cognitive impairments skew perceptions of personal networks

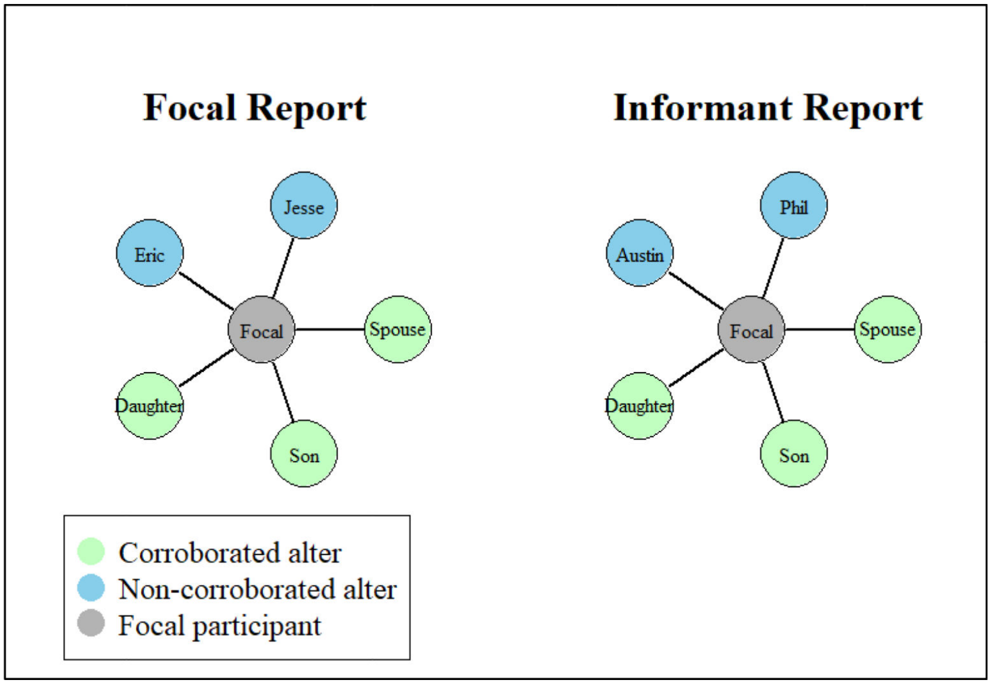

Figure 1.
Hypothetical illustration of focal-reported and informant-reported ego network

Note: Network corroboration equals $\frac{3}{(2+2+3)} = 0.43$ and network overlap equals $\left(\frac{3}{5}\right) \times 100 = 60\,\%$

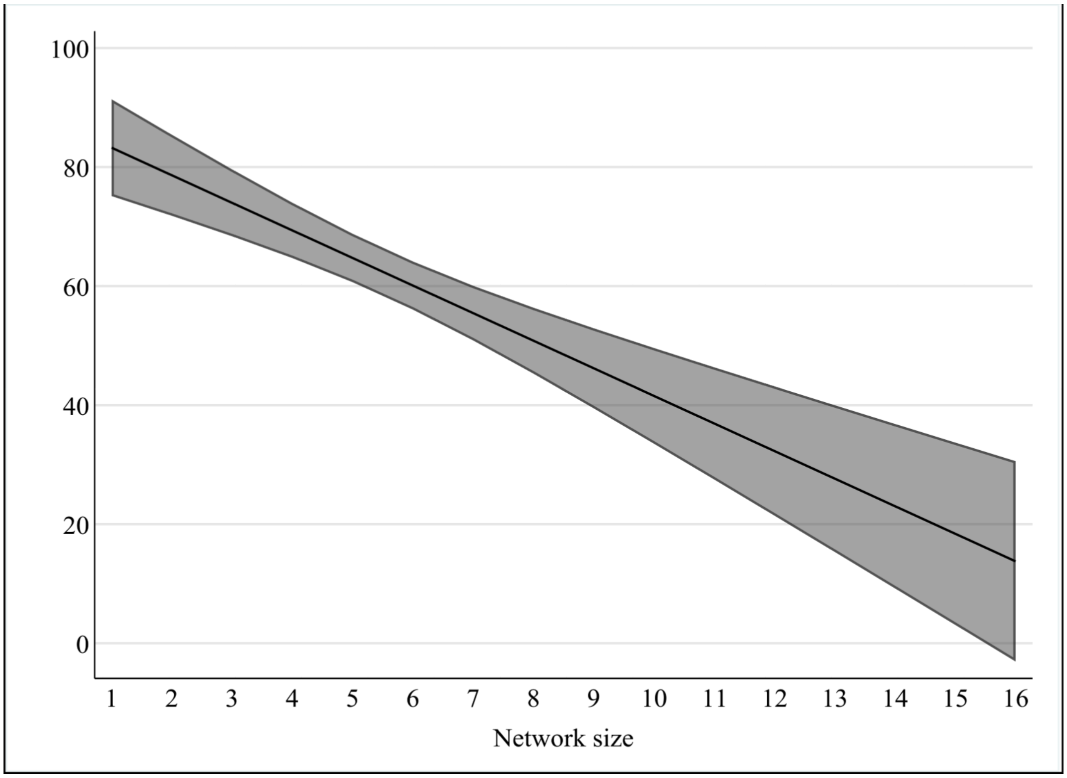

Figure 2.
Predicted values of overlap (%)

Note: Values derived from Table 3, Model 2.

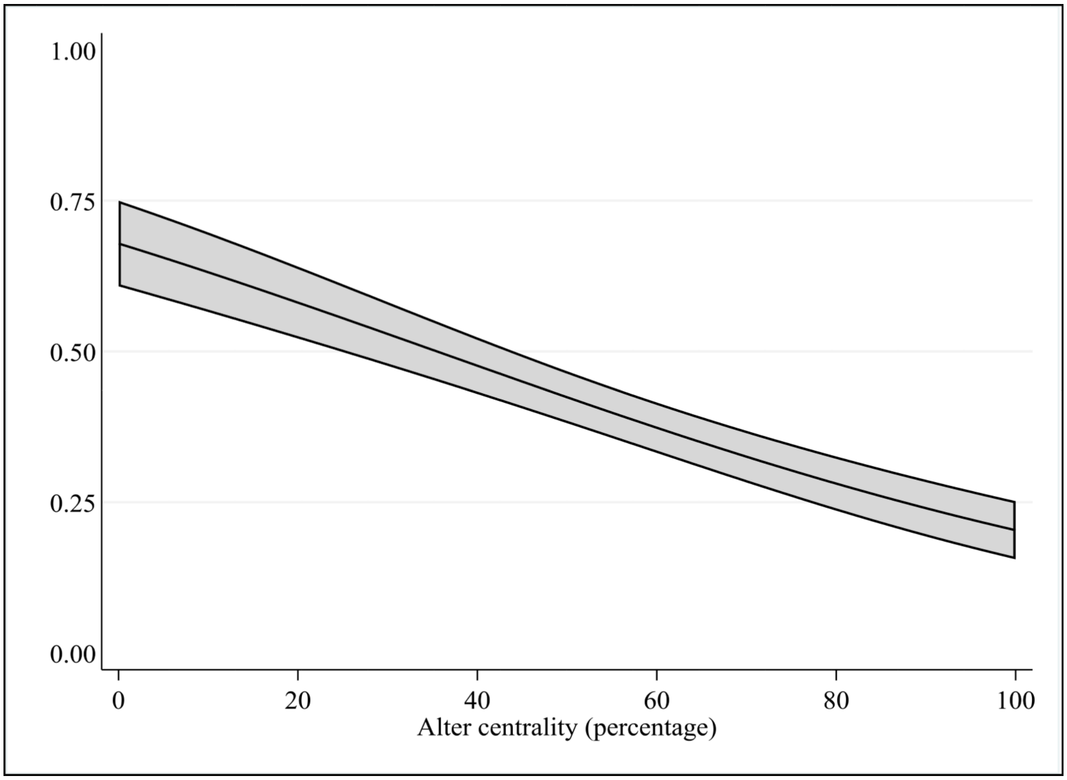

Figure 3.

Predicted probabilities of alter omission

Note: Probabilities derived from Table 5, Model 4.

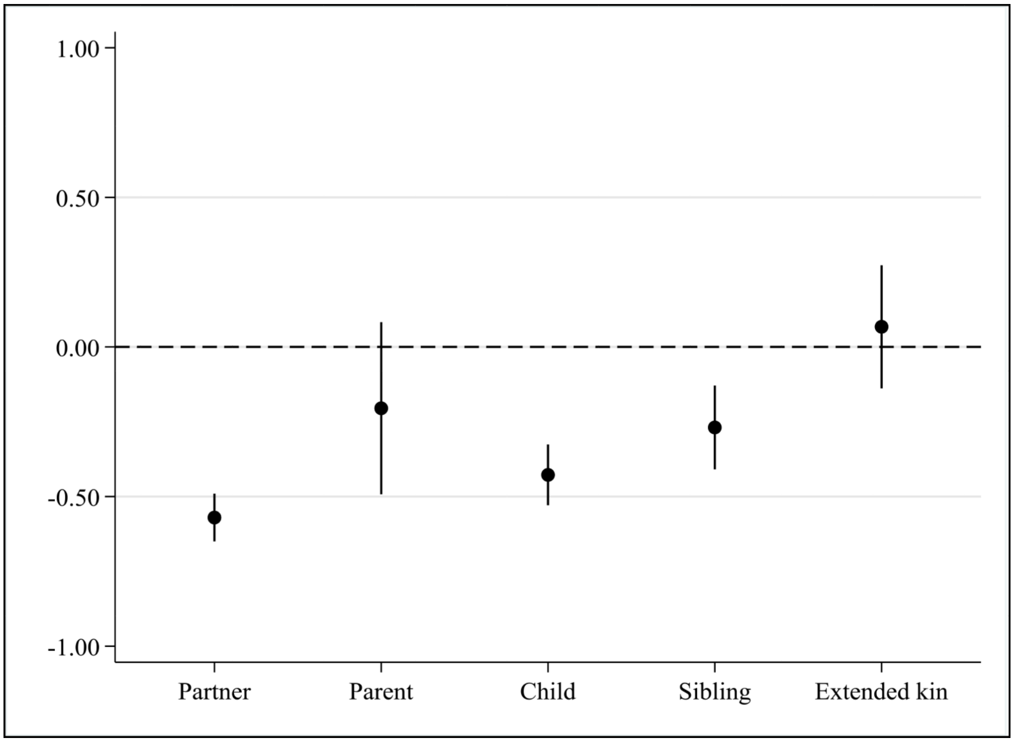

Figure 4.

Difference in predicted probabilities of alter omission by alter relationship (compared to non-kin)

Note: Probabilities derived from Table 5, Model 5. Confidence intervals are calculated using the delta method.

Table 1.

Descriptive Statistics (N=140)

	All (n=140)		*CN* (n=82)		*MCI* (n=29)		*Dementia* (n=29)		
	Mean/Prop	**SD**	**Mean/Prop**	**SD**	**Mean/Prop**	**SD**	**Mean/Prop**	**SD**	χ^2 / **F**
Network Accuracy									
Corroboration	0.47	(0.21)	0.46	(0.20)	0.52	(0.21)	0.45	(0.23)	1.23
Overlap (%)	65.22	(26.62)	61.98	(24.67)	76.22	(23.77)	63.37	(29.65)	3.24*
Network Attributes									
Network size (focal report)	4.89	(2.25)	5.28	(2.45)	4.31	(1.49)	4.38	(2.15)	3.61*
Density	0.64	(0.30)	0.58	(0.31)	0.73	(0.26)	0.70	(0.31)	3.93*
Percent kin	66.09	(28.32)	61.15	(27.92)	70.47	(28.69)	75.69	(26.77)	3.50*
Percent close	73.02	(26.37)	70.29	(26.66)	73.87	(28.09)	79.89	(23.15)	1.71
Percent freq. contact	69.22	(26.13)	67.42	(26.38)	71.68	(21.60)	71.84	(29.75)	0.49
Focal Attributes									
Female	0.58		0.70		0.55		0.62		10.83**
Age	71.97	(9.06)	71.10	(8.53)	73.99	(10.02)	72.43	(9.45)	1.04
Education (by years)	16.16	(2.70)	16.26	(2.54)	16.07	(2.52)	15.97	(3.32)	0.13
Co-residence	0.71		0.67		0.72		0.83		2.50

Notes: Network attributes are derived from focal participant’s self-report unless otherwise noted.

Table 2.

Linear regression predicting network corroboration

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
Ego Attributes												
Female	0.24	(0.19)	0.27	(0.19)	0.36*	(0.17)	0.25	(0.18)	0.17	(0.18)	0.22	(0.19)
Age (by decade)	−0.07	(0.09)	−0.08	(0.09)	−0.05	(0.09)	−0.09	(0.09)	−0.05	(0.09)	−0.06	(0.09)
Education (years)	−0.01	(0.03)	−0.00	(0.03)	0.01	(0.03)	−0.00	(0.03)	0.01	(0.03)	−0.01	(0.03)
Co-residence	0.16	(0.19)	0.21	(0.19)	−0.04	(0.18)	0.11	(0.19)	0.03	(0.18)	0.18	(0.19)
Diagnosis (ref: dementia)												
CN	−0.01	(0.24)	0.05	(0.24)	0.08	(0.21)	0.12	(0.24)	0.12	(0.22)	0.02	(0.24)
MCI	0.37	(0.27)	0.37	(0.28)	0.33	(0.24)	0.42	(0.26)	0.44	(0.24)	0.37	(0.27)
Network Attributes												
Network size			−0.07*	(0.03)								
Density					1.14***	(0.28)						
Percent kin (by 10s)							0.10***	(0.03)				
Percent very close (by 10s)									0.14***	(0.03)		
Percent freq. contact (by 10s)											0.05	(0.03)
Intercept	0.39	(0.91)	0.55	(0.93)	−0.83	(0.82)	−0.32	(0.88)	−1.04	(0.95)	−0.02	(0.90)
N	140		140		138		140		140		140	
R^2	0.04		0.07		0.16		0.13		0.17		0.06	

Note: The dependent variable (network corroboration) is standardized ($\overline{X} = 0$, SD=1). Network attributes are derived from focal participant's self-report. All models use robust standard errors

* $p < 0.05$

*** $p < 0.001$

Table 3.

Linear regression predicting network overlap

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
Ego Attributes												
Female	4.46	(5.30)	6.20	(4.99)	7.61	(4.75)	4.77	(5.14)	2.70	(5.00)	3.76	(5.20)
Age (by decade)	0.32	(2.63)	−0.34	(2.53)	0.47	(2.52)	−0.44	(2.62)	0.82	(2.66)	0.44	(2.54)
Education (years)	−0.57	(0.84)	0.15	(0.77)	0.00	(0.82)	−0.29	(0.78)	−0.08	(0.84)	−0.59	(0.84)
Co-residence	2.81	(5.30)	6.39	(5.08)	−3.67	(4.68)	1.29	(5.29)	−0.17	(4.96)	3.66	(4.97)
Diagnosis (ref: dementia)												
CN	−2.15	(6.60)	1.74	(6.51)	−0.54	(6.28)	2.31	(6.31)	1.05	(6.36)	−0.66	(6.49)
MCI	12.85	(7.43)	12.81	(7.24)	9.95	(6.24)	14.55*	(6.82)	14.54*	(6.84)	13.01	(7.43)
Network Attributes												
Network size			−4.63***	(0.79)								
Density					37.53***	(7.45)						
Percent kin (by 10s)							3.42***	(0.76)				
Percent very close (by 10s)									3.32***	(0.96)		
Percent freq. contact (by 10s)											2.53**	(0.86)
Intercept	66.17*	(25.55)	76.03**	(24.58)	34.50	(26.62)	42.37	(24.67)	31.37	(28.84)	47.01	(24.87)
N	140		140		138		140		140		140	
R^2	0.06		0.19		0.22		0.18		0.16		0.12	

Note: The dependent variable (network overlap) is measured as a percent ranging from 0 to 100. Network attributes are derived from focal participant's self-report. All models use robust standard errors

* $p < 0.05$

*** $p < 0.001$

Table 4.

Alter-level Descriptive Statistics

	Mean/Prop.	Mean/Prop.	Mean/Prop.	Mean/Prop.	F / χ^2
Focal Participant Perception					
	All (n=681)	*CN* (n=430)	*MCI* (n=125)	*Dementia* (n=126)	
Alter omitted (partner)	0.39	0.43	0.28	0.39	8.90^{*}
Alter relationship					12.65
Spouse/partner	0.15	0.14	0.16	0.18	
Parent	0.02	0.02	0.02	0.02	
Child	0.28	0.25	0.34	0.32	
Sibling	0.10	0.10	0.10	0.12	
Extended kin	0.05	0.05	0.06	0.06	
Non-kin	0.40	0.44	0.33	0.30	
Very close	0.71	0.68	0.74	0.81	6.52^{***}
Freq. contact (often)	0.65	0.63	0.72	0.67	3.45
Alter centrality (%)	58.74 (35.10)	52.95 (35.18)	68.95 (32.25)	68.53 (33.29)	16.69^{***}
Study Partner Perception					
	All (n=674)	*CN* (n=398)	*MCI* (n=147)	*Dementia* (n=129)	
Alter omitted (focal)	0.39	0.38	0.39	0.41	0.48
Alter relationship					25.73^{**}
Spouse/partner	0.12	0.12	0.12	0.13	
Parent	0.02	0.01	0.03	0.01	
Child	0.26	0.21	0.35	0.32	
Sibling	0.10	0.09	0.10	0.13	
Extended kin	0.06	0.06	0.06	0.07	
Non-kin	0.43	0.50	0.34	0.33	
Very close	0.68	0.69	0.69	0.67	0.22
Freq. contact (often)	0.64	0.67	0.67	0.54	6.99^{*}
Alter centrality (%)	57.89 (33.33)	53.06 (33.84)	63.61 (30.64)	66.35 (32.20)	10.76^{***}

Notes: Mean/proportions are presented (standard deviation in parentheses). Because the 'alter centrality' variable requires a network size of two or greater, this variable has 2 missing dementia cases on the focal participant's side and 1 missing CN case on the study partner's side.

* $p < 0.05$

** $p < 0.01$

*** $p < 0.001$

Table 5.

Logistic regression models predicting alter omission (Focal's perspective)

	Model 1		Model 2		Model 3		Model 4		Model 5	
	OR	**SE**	**OR**	**SE**	**OR**	**SE**	**OR**	**SE**	**OR**	**SE**
Ego attributes										
Female	0.82	(0.18)	0.86	(0.21)	0.82	(0.21)	0.66	(0.15)	0.72	(0.20)
Age (by decade)	1.00	(0.11)	0.95	(0.11)	0.98	(0.12)	0.98	(0.12)	1.05	(0.15)
Education (years)	1.04	(0.04)	1.01	(0.04)	1.05	(0.04)	1.00	(0.04)	1.01	(0.04)
Co-residence	1.00	(0.20)	1.11	(0.26)	0.97	(0.21)	1.29	(0.27)	1.26	(0.30)
Diagnosis (ref: dementia)										
CN	1.25	(0.31)	1.01	(0.27)	1.20	(0.34)	1.02	(0.27)	1.03	(0.30)
MCI	0.63	(0.20)	0.53	(0.17)	0.61	(0.23)	0.64	(0.20)	0.53	(0.20)
Network attributes										
Percent very close (by 10s)			1.02	(0.05)						
Alter is very close			0.18***	(0.05)						
Percent freq. contact (by 10s)					1.08	(0.05)				
Alter freq. contact					0.15***	(0.03)				
Alter centrality (%)							0.98***	(0.00)		
Percent kin (by 10s)									0.99	(0.05)
Alter relationship (ref: non-kin)										
Spouse/partner									0.03***	(0.01)
Parent									0.43	(0.26)
Child									0.14***	(0.04)
Sibling									0.32***	(0.10)
Kin (other)									1.36	(0.68)
Observations	681		681		681		679		681	
Pseudo R^2	0.01		0.10		0.12		0.10		0.20	
BIC	945.88		875.34		862.29		873.95		812.99	

Notes: Network attributes are derived from focal participant's self-report.

Table 6.

Logistic regression models predicting alter omission (Partner's perspective)

	Model 1		Model 2		Model 3		Model 4		Model 5	
	OR	**SE**	**OR**	**SE**	**OR**	**SE**	**OR**	**SE**	**OR**	**SE**
Ego attributes										
Female	0.87	(0.15)	0.91	(0.17)	0.88	(0.16)	0.80	(0.14)	0.78	(0.15)
Age (by decade)	1.08	(0.09)	1.09	(0.10)	1.10	(0.10)	0.99	(0.08)	1.05	(0.10)
Education (years)	0.99	(0.03)	0.99	(0.03)	0.99	(0.03)	0.96	(0.03)	0.98	(0.03)
Co-residence	0.86	(0.16)	0.93	(0.19)	0.92	(0.19)	0.93	(0.18)	0.95	(0.20)
Diagnosis (ref: dementia)										
Normal	0.90	(0.19)	0.90	(0.21)	0.97	(0.23)	0.71	(0.15)	0.85	(0.20)
MCI	0.89	(0.21)	0.90	(0.24)	0.96	(0.27)	0.86	(0.21)	0.91	(0.25)
Network attributes										
Percent very close (by 10s)			1.15***	(0.05)						
Alter is very close			0.13***	(0.03)						
Percent freq. contact (by 10s)					1.10*	(0.05)				
Alter freq. contact					0.23***	(0.04)				
Alter centrality (%)							0.98***	(0.00)		
Percent kin (by 10s)									0.97	(0.04)
Alter relationship (ref: non-kin)										
Spouse/partner									0.14***	(0.06)
Parent									0.84	(0.60)
Child									0.73	(0.20)
Sibling									0.91	(0.30)
Kin (other)									3.30**	(1.45)
Observations	674		674		674		673		674	
Pseudo R^2	0.00		0.11		0.07		0.06		0.07	
BIC	941.17		855.98		890.48		897.76		921.58	

Notes: Network attributes are derived from study partner's self-report.