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What kinds of social networks protect older adults' health during a pandemic? The tradeoff between preventing infection and promoting mental health

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ABSTRACT

When the coronavirus emerged in early 2020, older adults were at heightened risk of contracting the virus, and of suffering mental health consequences from the pandemic and from the precautions designed to mitigate it. In this paper, we examine how social networks *prior* to the pandemic helped to shape health beliefs, behaviors, and outcomes among older adults during its onset, focusing on (1) perceived risk of COVID-19, (2) preventative health behaviors, and (3) mental health, including loneliness, perceived stress, depression, and anxiety. Drawing on the longitudinal Social Networks in Alzheimer Disease study, we find that networks high in *bridging social capital* predict greater perceived risk and more precautions taken, but worse mental health. In contrast, networks high in *bonding social capital* predict less perceived risk and fewer precautions taken, but better mental health. We discuss this apparent tradeoff between physical and mental health.

As part of initial efforts to combat the spread of the coronavirus pandemic, U.S. health officials and political leaders urged the American people to stay home and practice social distancing whenever possible (Lee, 2020). The term "social distance" was intended to convey the physical space between individuals that was necessary to avoid spreading the virus. Yet this choice of wording evoked skepticism from mental health professionals who feared that the emotional connotations of the term would only further exacerbate the well-known difficulties of social isolation. Indeed, there were legitimate concerns that public calls for social distance would translate into a host of negative mental health outcomes (Allen et al., 2020). These concerns were especially heightened for older adults, a subpopulation that was identified early as an at-risk group (Span, 2020).

Threats of loneliness and social isolation were already prevalent among the older population well before the outbreak of the coronavirus pandemic. For instance, a pre-pandemic survey showed that upwards of 25% of older Americans experience loneliness at least some of the time (Wilson and Moulton, 2010). Given the demand for social interaction among this particular demographic, there were serious questions about whether older adults (a) were themselves concerned with contracting the COVID-19 virus through their interactions with others; (b) would willingly adhere to social distance policies; and (c) would experience any negative mental health outcomes in the effort to protect themselves and their loved ones from the virus. After all, social isolation itself results in a higher likelihood of mortality (Holt-Lunstad et al., 2015).

To address these issues, we explore the influence of personal social networks on the health beliefs, behaviors, and outcomes of a sample of community-dwelling older adults. Personal networks (the ties that connect an ego to his or her alters, and the ties between the alters themselves) are important for understanding health and health-related behaviors because they expose individuals to a group of people who collectively offer emotional and instrumental support, enforce social norms, and provide access to novel information and perspectives (Perry et al., 2018). Because all individuals are situated within a personal network that is unique to themselves, they are expected to derive different benefits and detriments depending on the combination of people within their network and the interconnected structure of ties among these people.

Our findings suggest that the protective factors associated with good mental health for these individuals, such as strong, tight-knit networks, might also be associated with less perceived risk about the pandemic and more risk-taking behavior. In contrast, factors that might encourage diligence regarding the virus—broad networks with weak ties through which health information is disseminated—might be associated with

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greater worry, more self-imposed isolation, and worse mental health. Drawing on a sample of older adults from the Social Networks in Alzheimer Disease (SNAD) study, we examine evidence relevant to the alleged tradeoff between physical and mental health, and how social networks may relate to these health beliefs, behaviors, and outcomes.

Background

Social networks provide multiple resources that may translate into health-related advantages. Here, we focus on two key resources: *bonding capital* and *bridging capital*. In the following sections, we summarize the broad literature on social network predictors of health and demonstrate the likely importance of these resources in the context of the pandemic. We focus on three areas of health: (1) risk perception, (2) health precautions, and (3) mental health consequences of the pandemic. By examining the social network predictors of these health attitudes, behaviors, and outcomes—as well as the mechanisms underlying these relationships—we illuminate key structural pathways that have been underexplored with respect to the coronavirus.

Network resources: bonding and bridging capital

Tight-knit social networks are often associated with better mental health because close, kin-centered relationships provide a high degree of structural support—what scholars refer to as "bonding social capital" (Putnam, 1995; Lin, 2002; Turner and Turner, 2013). As early as Durkheim (1897), scholars have argued that dense, highly integrated networks offer the kind of cohesion and security necessary to support mental health. Such networks allow individuals to feel rooted in their community and committed to something other than themselves (see also Ashida and Heaney, 2008). While too much insularity (e.g., a network comprising only family members) can be harmful to mental health (Fiori et al., 2006; Litwin and Shiovitz-Ezra, 2011), tight-knit networks generally offer a high degree of emotional and instrumental support.

Yet during a pandemic, these same factors that are protective of mental health may also place individuals at greater *physical* health risk. Individuals with kin-centered, tight-knit networks may have less exposure to novel information that can be a crucial source of adaptation when a new health threat arises (Freese and Lutfey, 2011; see also Moon et al., 2019). Moreover, lacking the weak ties that offer access to diverse and emerging perspectives, such individuals may fail to perceive the risks associated with a new pathogen like COVID-19. If those with tight-knit networks feel less worried, and if they lack novel information about the risks that the virus presents, they may be less likely to engage in precautions that protect themselves and others. To be sure, calculations of risk are also based on the likelihood of exposure (Wildavsky and Dake, 1990), and it is possible that individuals with smaller or more homogenous networks may be making a rational calculation that they have less to fear from the virus. While this is not necessarily problematic, for at least some older adults these calculations may overestimate their protection from COVID-19 and contribute to overconfidence or insufficient behavioral modification.

In contrast, individuals with broader, more diverse networks have the advantage of "bridging social capital"—the set of benefits that accrue from expansive network ties. (Granovetter, 1973; Gittell and Vidal, 1998; Burt, 1992; Kawachi et al., 2008; Cornwell, 2009). While networks can be a source of stress, they can also convey crucial information about the severity of a health risk and health behaviors designed to mitigate such risk (Pescosolido, 1992, 2011; Freese and Lutfey, 2011; McConnell, 2017). It is precisely "when new diseases, risks, and knowledge about risks emerge" that perceptions and attitudes about health, along with proactive health behaviors, become powerful determinants of inequalities in health outcomes—and these perceptions, attitudes, and behaviors are heavily shaped by social networks (Shim, 2010:3; Link and Phelan, 1995).

In what follows, we turn to the broader literature on social networks and health, focusing on three areas related to the coronavirus: risk perception, health precautions, and mental health outcomes. We argue that the effects of social networks on these health-related measures may be explained, at least in part, by the two forms of capital—bonding and bridging—that individuals' networks confer. We further suggest that because the characteristics of bridging and bonding networks are somewhat distinct, there may be a tension between the mental health benefits provided by bonding capital and the physical health guidance provided by bridging capital.

Social network predictors of perceived risk and precautionary behaviors

During the initial phases of COVID-19, general surveys of major pandemic-related worries showed that delayed access to hospital care for emergency conditions, unemployment consequences from an economic downturn, and mental health concerns associated with lockdowns and decreased social engagement were among the general public's top concerns (Coelho et al., 2020). Yet these concerns were not equally distributed across society. For instance, Barber and Kim (2021) found that older adults, ages 65–81, tended to perceive the risks of COVID-19 to be higher than their young adult counterparts, ages 18–35. Additionally, the perceived risks of the coronavirus were lower among men than women for both the older and younger age groups.

Such risk perceptions are often treated as individual, isolated phenomena unconnected to a larger social system (Wildavsky and Dake, 1990). However, social networks can influence individuals' perceptions of risk in multiple ways. First, risk perception can diffuse through social networks from person to person similar to infectious disease contagion. For example, Scherer and Cho (2003) found that the perceived risks associated with a nearby hazardous waste clean-up site were more similar among those interpersonally connected to one another (see also Muter et al., 2013). Similarly, in a study of HIV risk, social interactions were found to have a causal influence on risk perception and behavioral change (Kohler et al., 2007). Research on health behavior suggests that the role of social networks in shaping and amplifying risk perceptions is particularly strong in the context of a high level of uncertainty about a disease and about optimal behavioral responses (Petts and Niemeyer, 2004).

Second, the structure and composition of social networks may shape concerns about COVID-19 that are fueled by fear for the well-being of others. For example, people with networks that contain older individuals may worry more about the pandemic because their loved ones are at disproportionate risk for hospitalization and death. Zhou and Guo (2021) conducted a large survey in China and found that those who were married and those living with a large family were generally more worried about COVID-19. The authors reasoned that married people and large families have to worry about more loved ones, such as children and aging parents, which can contribute to a greater overall concern about COVID-19. Despite traditionally being a source of support, larger family structures have become a worry-inducing burden during the COVID-19 pandemic. Additionally, people with larger networks may have heightened concern about COVID-19 because being embedded in these networks is associated with increased risk for exposure through a broader set of secondary social contexts and contacts.

Third, social networks may affect COVID-19 worry due to exposure to the adverse consequences of the disease (Herrera-Diestra and Meyers, 2019). Individuals who have personally known people that were hospitalized or died from COVID-19 are likely to be more worried having witnessed these consequences firsthand. This particular social phenomenon is well understood and has been a critical component for infectious disease modeling. For example, in constructing a model for infection dynamics of the avian flu, Bagnoli et al. (2007) positively correlate risk perception to the fraction of neighbors that are ill. Indeed, the direct visibility of a crisis is among the strongest motivators of risk perception, and subsequently of preventative behavior and epidemic control (Herrera-Diestra and Meyers, 2019). People with larger, more diverse, and more at-risk networks are likely exposed to more adverse consequences of the pandemic.

Just as they shape attitudes about health, social networks can also constrain behavior, serving as a source of social regulation by pushing individuals toward (or away from) health-promoting activities (House et al., 1988; Umberson, 1992; Smith and Christakis, 2008). Networks linked to bonding capital may be especially adept at encouraging behavioral modification, because strong, kin-centered relationships exert more normative influence—but whether these behaviors are healthy or harmful depends on the content of the norms themselves. As Moon et al. (2019) found in a study of infant sleep practices, risky behaviors such as the placement of a child on her stomach were more common in "exclusive" networks (those with more kin and stronger ties) than in "expansive" networks (those with weaker and sparser ties), because the pressure to accept advice and distrust medical guidelines was harder to resist when alters were close kin. In contrast, mothers with "expansive" networks were more likely to follow healthy practices because of their exposure "to a variety of opinions and more sources of health-relevant information" (Moon et al., 2019:156).

Particularly in the context of public health crises, bridging social capital provides an avenue by which helpful health information can flow through social networks, providing individuals within the network the necessary information and awareness needed to mitigate the spread of disease. This mechanism was exemplified by Chuang et al. (2015), who found during an influenza pandemic that bridging social capital was associated with positive health behavior, such as intention to wear a mask. Increasing community-level bridging capital aids in constructing the social infrastructure necessary to effectively respond to infectious disease outbreaks. However, Chuang and colleagues also found that bonding capital was associated with alternative preventative behaviors, such as intention to receive a vaccination and more frequent handwashing. Thus, there may be a synergism between the two forms of social capital that together contribute to increased adoption of preventative health behaviors. Just as bridging capital can improve health behaviors by offering novel sources of information, so too can bonding capital encourage such behaviors by exerting normative pressure on individuals to follow recommended guidelines.

Examination of the current literature shows that an individual's risk perception and preventative health behaviors are significantly influenced by social networks, but whether these influences are salutary or harmful is not always easy to predict. Within the context of the COVID-19 pandemic, the extent to which bridging and bonding social capital confer physical health protection from the virus remains relatively understudied. *Thus, we examine how social network characteristics are associated with an individual's risk perception and health precautions taken against COVID-19.*

Mental health and social networks

Given that later life is characterized by the departure from meaningful social roles, desire for quality social interactions, and increased likelihood of health declines, older adults tend to exhibit a heightened dependence on their personal social networks (Carstensen, 1992; Marshall and Bengtson, 2011; Cornwell and Schafer, 2016; Roth, 2020). Consequently, the social distancing practices of the pandemic may have placed older adults at particularly high mental health risk, due to the imposition of lockdowns and limited social interactions. Numerous studies have been conducted regarding the loneliness and mental health of older adults as well as the general population during the COVID-19 pandemic. While some studies do find an increase in loneliness and other mental health problems among older adults (Lee et al., 2020; Krendl and Perry, 2021; Bailey et al., 2021), others have contrastingly found that older adults exhibit a resilience to pandemic-related trauma relative to their younger adult counterparts (Vahia et al., 2020; Igarashi et al., 2021; see also Peng and Roth, 2021).

This heterogeneity in mental health outcomes among members of this age group suggests there may be certain types of network configurations that better lend themselves to preserving mental health during this time. Indeed, similar periods of hardship reveal the crucial influence of social networks on mental health: During crises or stressful external shocks, individuals' social networks tend to decrease in breadth and shrink overall as individuals begin to focus more on closer network ties (Romero et al., 2016). This may serve an adaptive function: While the pandemic brought an increase in loneliness due to social isolation, those who shifted their attention to close network ties may have experienced a smaller increase in loneliness (Kovacs et al., 2021). This transition from networks with bridging characteristics, evidenced by large network sizes and weak ties, to bonding characteristics that emphasize the maintenance of close ties, acts much like a social feedback loop which attempts to maintain homeostasis in regard to mental health.

Regardless of the adaptations that individuals made in response to the pandemic, previous research leads us to suspect that even network characteristics *prior* to the pandemic may have helped shape individuals' mental health once the coronavirus and the policy changes that followed were underway. *Our final aim is to examine whether social network characteristics before the pandemic are associated with mental health outcomes in the early months of the outbreak.*

Data & methods

Data

We use data from the Social Networks in Alzheimer Disease (SNAD) study. The SNAD study was developed in concert with the Indiana Alzheimer's Disease Research Center (IADRC) to study the social determinants of cognition in an aging population. Members of the IADRC patient population (all Indiana residents) were assessed for various signs of cognitive function and cognitive decline, along with brain imaging measures; exclusion criteria include history of schizophrenia, bipolar disorder, or other major psychiatric disorders; history of cancer with chemotherapy or radiation treatment; traumatic brain injury with loss of consciousness; developmental disabilities; and history of or active alcohol/substance abuse disorders. Respondents were then invited to participate in SNAD, a face-to-face interview in which individuals were asked a detailed set of questions about their social networks. Additional exclusion criteria for SNAD include IADRC participants with a Montreal Cognitive Assessment (MoCA) score below 10[1]; age below 45; known family history of dominantly inherited dementia genes, such as APP, GSS, and PSEN-1; and Prion disease.

Because SNAD is a longitudinal study, some respondents have completed as many as five interviews. For baseline data—which includes our social network measures—we use the *most recent interview* conducted prior to the pandemic for which the respondent provided complete social network data. Interview dates range from July 2016 to early March 2020, with the last interview on March 3. Given the timing of data collection, the reader should generally not be concerned about reverse causation (i.e., effects of the pandemic on social networks).

At the onset of the coronavirus outbreak, SNAD participants were invited to a follow-up interview about their response to the pandemic. This interview, conducted by telephone from April to June 2020, included questions about respondents' health precautions, fears about the virus, and overall mental health, among other topics. Of 320 respondents who participated in the original SNAD survey, those who had not discontinued the study or passed away (n = 266) were contacted for follow-up, and 142 completed the COVID-19 supplement. For the following analyses, we dropped those who had not completed the full social network battery (n = 14) and those with missing data on

[1] MoCA scores below 10 indicate severely limited cognitive function; such individuals have been excluded because they may not be able to reliably report on their social networks.

remaining variables of interest (n = 15), for a total analytic sample of 113 respondents. Note that the time between the pandemic interview and the most recent pre-pandemic interview varies across respondents, with a median of 16 months between interviews and a range of 2–47 months. Adjusting for these differences does not affect our findings (see Tables S1–S3 online).

Measures

Dependent variables

COVID-19 risk perception. Respondents were asked about their perceptions of the COVID-19 pandemic, such as their worries about catching the virus. For each item, respondents could answer 1 "Strongly Agree", 2 "Agree", 3 "Disagree", or 4 "Strongly Disagree." Items included the following: (1) If I do not do anything to avoid getting COVID-19, I am likely to catch it; (2) I am worried about catching COVID-19; (3) I am worried about becoming seriously ill, being hospitalized, or dying from COVID-19; (4) I am worried that people I care about will catch COVID-19; (5) I am worried that people I care about will becoming seriously ill, be hospitalized, or die from COVID-19. Responses to these items are reverse-coded so higher scores reflect greater perceived risk, and a scale is constructed by computing the mean across all 5 items and standardizing the result. Cronbach's alpha is $\alpha = 0.80$.[2]

COVID-19 health precautions. Respondents were asked which precautions they have taken as a result of the pandemic "to prevent yourself or people in your household from getting COVID-19." Responses were coded into 11 possible categories: (1) Cleaned or disinfected (2) Washed hands or reminded others to wash hands (3) Wore a mask, gloves, or other protective gear (4) Avoided touching face, mouth, nose, eyes (5) Stocked up on food, toilet paper, or other essential goods (6) Had food, medicine, or other essential goods delivered instead of going out (7) Worked from home (8) Avoided public gatherings, events, and places (9) Canceled planned social events (10) Canceled planned travel (11) Other. Because our sample comprises older adults, most of whom are no longer working, we exclude the option "Worked from home" and compute the sum of the remaining ten.

Mental health. We utilize four mental health scales based on responses to the COVID-19 supplement. *Loneliness* (adapted from Hughes et al., 2004) is computed as the mean of three items, with values 1 "Strongly Agree", 2 "Agree", 3 "Disagree", or 4 "Strongly Disagree." Respondents were asked how much they agree or disagree about feelings of loneliness they may have experienced over the past 30 days: (1) I often feel that I lack companionship (2) I often feel left out (3) I often feel isolated from others. Items are reverse-coded so higher scores reflect greater loneliness, and a scale is constructed by computing the mean across all 3 items and standardizing the result. Cronbach's alpha is $\alpha = 0.71$.

Perceived stress includes four items from the Perceived Stress Scale (Cohen et al., 1983). Respondents were asked how often, during the last two weeks, they felt various emotions, from 1 "Not at all" to 4 "Nearly every day." The items are as follows: (1) How often have you been upset because of something that happened unexpectedly? (2) How often have you felt stressed? (3) How often have you felt that things were not going your way? (4) How often have you been unable to control irritations in your life? Items are coded so higher scores reflect greater perceived stress, and a scale is constructed by computing the mean of the four items and standardizing the result. Findings derived from the PSS must be interpreted with caution, since our measure of perceived stress only contains four of the items from the original ten-item scale, and this subset has not been validated to our knowledge. However, the scale has reasonable internal consistency given the small number of items (Cronbach's alpha is $\alpha = 0.67$).

Depression is derived from the 5-item Geriatric Depression Scale (GDS-5; Hoyl, . et al., 1999). Items from the GDS include: (1) In general, are you basically satisfied with your life? (2) Do you often get bored? (3) Do you often feel helpless? (4) Do you prefer to stay at home rather than going out and doing new things? (5) Do you feel pretty worthless the way you are now? Items are coded 0 = No and 1 = Yes (the first item is reverse-coded), and the total is calculated by computing the sum of the five items.

Finally, *anxiety* is a four-item measure adapted from the anxiety subscale of the Hopkins Symptom Checklist (Derogatis et al., 1974; see Simonsick et al., 1999 for precedent). Items from the anxiety checklist ask about feelings during the last week: (1) Did you feel nervous or shaky inside? (2) Did you have to avoid certain things, places, or activities because they frightened you? (3) Did you feel tense or keyed up? (4) Did you feel fearful? Items are coded 0 = No and 1 = Yes, and the total is calculated by computing the sum of the four items.

Independent Variables

The SNAD study uses two name-generating prompts that elicit the members of each respondent's social network: one that asks respondents about people with whom they discuss "important matters," and another that asks respondents about people with whom they discuss "health matters" (see Perry et al., 2018). Respondents completed the PhenX Toolkit Social Network Battery (Perry and Pescosolido, 2010; Hamilton et al., 2011) to answer questions about relationships between each respondent (ego) and their network members (alters), and between alters themselves (see Table S4 online for details). In this study, we leverage 10 network variables that were collected during the most recent *pre-pandemic* interview, and divide them into two theoretically distinct categories.[3] The first set of measures centers on *social bonding*, and includes network density, proportion kin, proportion close, proportion frequent contact, mean support functions, and mean tie strength. These measures capture the extent to which respondents have dense, tight-knit, family-centered networks. *Network density* is the mean closeness of the tie between alters (each tie has a possible closeness of 0–3). *Proportion kin* is the proportion of alters in the network who are related to ego. *Proportion close* is the proportion of alters in the network with whom ego has a very close relationship. *Proportion frequent contact* is the proportion of alters in the network with whom ego is in frequent contact (seeing or talking to the alter "often" rather than "occasionally" or "hardly ever"). *Mean support functions* refers to the average number of support functions that alters provide to ego, such as financial help, practical advice, or emotional comfort (range: 1–5). *Mean tie strength* refers to the average strength of the tie between ego and each of the alters (range: 1–10). While tie strength is similar to tie closeness, the latter can imply a degree of intimacy that is absent from some strong ties (especially family ties); we use both mean tie strength and proportion close to capture these distinct phenomena.

The second set of measures centers on *social bridging*, and includes network size, effective size, diversity, and strength of weakest tie. These measures capture the extent to which respondents have broad, expansive networks that may connect them to novel information and social stimuli. *Network size* is the number of alters in ego's network. While core network size does not vary much among older adults (Cornwell et al., 2008), *overall* network size may capture additional peripheral ties that provide access to bridging capital. Our study uses a variety of name

[2] The scale originally included eight items, but we dropped the last three items due to the lower Cronbach's alpha value. Results do not change substantially.

[3] To be sure, many of these network measures could be classified as bridging *or* bonding depending on their value. For example, low density is associated with bridging due to the presence of structural holes (Burt, 2002), while high density is associated with bonding due to the tight-knit nature of the network.

generators that elicit both core and peripheral networks. *Effective size* refers roughly to the number of non-overlapping groups with which a person interacts; it is calculated as the number of alters minus the mean number of ties that each alter has to all other alters. *Diversity* refers to the number of unique relationship types in a person's network (Cohen et al., 1997), and includes the following possibilities: (1) spouse/partner (2) parent, (3) brother/sister (including stepbrothers and stepsisters), (4) child, (5) grandparent, (6) grandchild, (7) aunt or uncle, (8) in-law, (9) other relative, (10) coworker or colleague, (11) neighbor, (12) friend, (13) boss, employer, or teacher, (14) employee, (15) fellow student (went to school together), (16) lawyer, (17) doctor, (18) other medical professional, (19) counselor or mental health therapist, (20) priest, minister, or rabbi, (21) fellow church member, (22) member of same club or social group, or (23) partner for leisure activities. We count the number of unique relationship types in each respondent's network and *divide by network size* to avoid conflating diversity with overall size of the network. Finally, *strength of weakest tie* refers to the tie between ego and his or her most weakly connected alter (range: 1–10). A high score on this item indicates the absence of a weak tie in the network.

Covariates

In all models, we control for respondents' gender (0 = male, 1 = female), age during the COVID-19 interview, educational attainment (measured as the number of grades completed), and living situation during the pandemic (living alone or with others). We considered including marital status, but living situation is a strong proxy, with a tetrachoric (binary) correlation of –0.65; we include only living situation because it has a stronger theoretical relationship with mental health outcomes such as loneliness. Finally, we add the respondent's Geriatric Depression Scale (GDS-15) score and anxiety score from the most recent pre-pandemic interview to control for baseline mental health. These baseline measures are more comprehensive than those administered in the pandemic follow-up: the GDS-15 (Yesavage, 1988) contains all fifteen items, rather than five in the follow-up, while the four anxiety items from the Hopkins Symptom Checklist are ordinal (0–3), rather than binary in the follow-up. See Tables 1a 1b for a full set of descriptive statistics and correlations.

In supplementary models (available in Tables S1–S3 online), we also control for cognitive status determined by IADRC clinical consensus (0 = cognitively normal, 1 = mild cognitive impairment or dementia) and the number of months between the most recent pre-pandemic interview and the COVID-19 supplement (median: 16 months). Because coefficients do not change significantly when these measures are added, we show the more parsimonious models in our main results to maximize statistical power.

Timing of measurement

Measures collected *at baseline* (the most recent interview prior to the pandemic) include all social network measures along with gender, educational attainment, baseline depression, baseline anxiety and, in supplementary analyses only, cognitive status. Measures collected *during the pandemic* include all outcomes (COVID-19 risk perception, COVID-19 health precautions, loneliness, perceived stress, depression, and anxiety) along with age, living situation and, in supplementary analyses only, months since the prior interview.

Analytical approach

In the analyses that follow, we assess the relationship between social network measures collected prior to the pandemic and COVID-19–related outcomes collected in April–June 2020. For each of the six outcomes of interest—COVID-19 risk perception, COVID-19 precautions, and mental health outcomes including loneliness, perceived stress, depression, and anxiety—we introduce each social network measure as an independent variable (but in separate models to avoid issues of multicollinearity). We also include the following covariates: respondent gender, age, educational attainment, living situation (living alone or with others), and baseline mental health (depression and anxiety). The inclusion of pre-pandemic depression and anxiety allows us to distinguish outcomes that are the result of the pandemic from those that existed prior to the pandemic—for example, social networks may have an influence on COVID-19–related anxiety and depression, but by controlling for prior mental health we ensure that the effects are at least partially due to the pandemic and are not a mere residue of prior mental health challenges. Ideally, we would include a prior measure of *every* mental health outcome, including loneliness and perceived stress, but data limitations prevent us from doing so.

To accommodate a diverse set of dependent variables, we employed several estimation strategies. Models with a continuous outcome—the risk perception scale, loneliness scale, and perceived stress scale—are fit via ordinary least squares (OLS) regression. Models with a count outcome—health precautions, depression, and anxiety—are fit via binomial

Table 1a
Descriptive Statistics (N = 113).

	Mean/ Prop.	SD	Min	Max
<u>*Outcomes*</u>				
COVID-19 risk perception scale	2.75	.58	1.00	4.00
COVID-19 precautions taken	7.21	1.45	4	10
Loneliness	2.11	.64	1.00	3.67
Perceived stress	1.44	.48	1.00	3.00
Geriatric depression scale (GDS-5)	.79	1.05	0	4
Anxiety	.79	.98	0	4
<u>*Bonding Social Capital*</u>				
Mean closeness of the tie between alters ("density")	1.63	.70	.00	3.00
Proportion of alters who are kin to ego ("proportion kin")	.62	.27	.00	1.00
Proportion of alters who are "very close" to ego ("proportion close")	.77	.25	.00	1.00
Proportion of alters who ego sees or talks to "often" ("proportion frequent contact")	.68	.24	.00	1.00
Mean number of support functions (up to 5) that alters provide to ego ("mean support functions")	2.96	.60	1.14	4.67
Mean strength of tie between ego and each of the alters ("mean tie strength")	8.41	1.11	5.40	10.00
<u>*Bridging Social Capital*</u>				
Network size	5.85	2.64	2	17
Network size minus mean number of ties between alters ("effective size")	2.38	1.64	1.00	8.75
Network diversity (number of unique relationship types) divided by network size	.68	.21	.29	1.25
Strength of tie between ego and the most weakly connected alter ("strength of weakest tie")	6.57	2.33	1	10
<u>*Gender*</u>				
Male	.30			
Female	.70			
Age at COVID-19 interview	72.59	7.00	57	93
Months since prior interview	17.42	11.86	2	47
Education (grades completed)	16.59	2.44	12	21
<u>*Diagnosis*</u>				
Cognitively normal	.80			
Mild cognitive impairment or dementia	.20			
<u>*Living Situation at COVID-19 Interview*</u>				
Living alone	.24			
Living with others	.76			
Geriatric depression scale (GDS-15) at baseline	1.58	1.69	0	8
Anxiety at baseline	.52	.59	.00	2.75

Notes: (a) Scores on baseline depression and anxiety are not comparable with scores during the COVID-19 follow-up interview, because the measures are distinct. See "Data & Methods" for further details. (b) Min and max are *observed* (based on the empirical data), not theoretical.

Table 1b
Correlation Matrix.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1. COVID-19 Risk Perception Scale																				
2. COVID-19 Precautions	.33[a]																			
3. Isolation	.07	.04																		
4. Perceived Stress	.06	.00	.31[a]																	
5. Anxiety	.26[b]	.07	.17	.42[a]																
6. GDS-5	-.04	-.01	.32[a]	.37[a]	.44[a]															
7. Density	-.10	-.24[c]	-.17	-.15	-.15	-.04														
8. Network Size	.09	.39[a]	-.12	.01	.04	.00	-.32[a]													
9. Effective Size	-.00	.31[a]	-.02	-.00	.07	-.02	-.65[a]	.74[a]												
10. Diversity (Adjusted for Network Size)	.02	-.06	-.04	.19[c]	.16	.13	-.00	-.44[a]	-.30 * *											
11. Proportion Kin	.02	-.20[c]	-.11	-.05	-.02	.09	.66[a]	-.28[b]	-.49[a]	.05										
12. Proportion Close	-.10	-.16	-.16	-.03	.04	-.10	.30 * *	-.15	-.24 * *	.05	.21[c]									
13. Proportion Frequent Contact	-.04	.02	-.16	.09	.17	-.04	.25 * *	-.06	-.19[c]	.09	.15	.28 * *								
14. Mean Support Functions	-.01	-.03	-.07	.01	-.15	-.26 * *	.20[c]	-.16	-.21[c]	.06	.10	.07	.34[a]							
15. Mean Tie Strength	-.24 *	-.16	-.25 * *	-.07	-.12	-.23[c]	.31[a]	-.09	-.14	.00	.17	.51[a]	.24[c]	.29 * *						
16. Strength of Weakest Tie	-.26[b]	-.29[b]	-.23[c]	-.02	-.18	-.21[c]	.41[a]	-.34[a]	-.34[a]	.11	.19[c]	.42[a]	.26[b]	.30[b]	.81[a]					
17. Age at COVID-19 Interview	-.12	-.17	.12	-.30 * *	-.14	.02	.07	-.20[c]	-.16	-.01	-.09	.02	-.15	-.12	-.09	.03				
18. Months Since Prior Interview	.06	-.06	.02	-.01	-.15	-.17	.01	-.19[c]	-.08	.12	-.07	-.19[c]	.06	.29 * *	-.09	.10	.08			
19. Education (Grades Completed)	.04	.23[c]	-.08	.10	-.11	-.13	-.09	.15	.21[c]	-.01	-.14	-.13	-.01	-.09	-.18	-.12	-.14	.02		
20. GDS-15 at Baseline	.03	-.11	.23[c]	.24[b]	.33[a]	.43[a]	.08	-.17	-.14	.12	.18	-.05	-.07	-.17	-.16	-.14	-.10	-.12	-.12	
21. Anxiety at Baseline	.04	-.08	.10	.31[a]	.29[b]	.06	-.00	-.12	-.09	.05	.12	-.09	.05	.11	-.01	-.06	-.25 * *	-.06	-.16	0.30[b]

[a] $p < 0.001$
[b] $p < 0.01$
[c] $p < 0.05$

regression: We use generalized linear models (GLM) with a logit link function and a binomial distribution, allowing us to specify the maximum possible score for each measure. (Alternative estimators, such as negative binomial regression, may not be appropriate because they ignore the upper bound on these measures; see Wooldridge 2010:739–40.) We present average marginal effects from these models—e.g., average change in the number of health precautions taken—for ease of interpretation. All models are estimated using StataMP 17.0.

In total, we fit 60 models: 6 outcomes × 10 network variables. We address concerns about multiple testing in the Discussion. Note that in Tables 2–4 below, we do not provide coefficients on covariates given the large number of individual models fitted. However, we provide a table online (Table S5) that shows the effect of covariates on dependent variables when no network measures are included.

Results

COVID-19 risk perception

Table 2 examines the association between social network predictors and COVID-19 risk perception, a standardized scale comprising five items; effect sizes are reported as OLS coefficients. We find that two network measures—*mean tie strength* and *strength of weakest tie*—are associated with significantly less perceived risk about the virus. Controlling for covariates, one standard-deviation (SD) increase in mean tie strength (the average strength of the relationship between the respondent and his or her alters) predicts a 0.29 SD drop in perceived risk ($p < .01$), and a one-SD increase in the strength of the weakest tie predicts a 0.27 SD drop in perceived risk ($p < .01$). High scores on mean tie strength indicate the presence of *bonding capital*, the advantages that accrue from strong, tight-knit networks, while high scores on strength of weakest tie indicate the absence of bridging capital.

COVID-19 precautions

In Table 3, we report the association between social networks and the number of COVID-19 precautions taken. Because we estimate these models using binomial regression, coefficients reported here are average marginal effects (AMEs) rather than logged odds, for ease of interpretation.

Five network measures are significantly associated with COVID-19 precautions taken, conditional on covariates. Network characteristics that predict more COVID-19 precautions—such as handwashing and avoiding travel—are *network size and effective size*. Net of covariates, a one-SD increase in network size is associated with 0.54 more precautions taken ($p < 0.001$); a one-SD increase in effective size (roughly,

Table 2
Do Social Networks Predict COVID-19 Risk Perceptions?.

	Risk Perceptions
Bonding Social Capital	
Density	-.08 (.09)
Proportion Kin	.02 (.10)
Proportion Close	-.12 (.10)
Proportion Frequent Contact	-.07 (.09)
Mean Support Functions	-.03 (.10)
Mean Tie Strength	-.29 (.10)* *
Bridging Social Capital	
Network Size	.08 (.13)
Effective Size	-.03 (.11)
Diversity (Adjusted for Network Size)	.04 (.10)
Strength of Weakest Tie	-.27 (.10)* *

* $p < 0.05$; * * $p < 0.01$; * ** $p < 0.001$ (*Two-tailed tests*)Notes: (a) Covariates include gender, age, education, living situation, and baseline depression and anxiety. (b) Social network measures and the risk perception scale are both standardized. (c) Robust standard errors in parentheses.

Table 3
Do Social Networks Predict COVID-19 Precautions Taken? (Average Marginal Effects from Binomial Regression).

	COVID-19 Precautions
Bonding Social Capital	
Density	-.27 (.13)*
Proportion Kin	-.22 (.14)
Proportion Close	-.25 (.14)
Proportion Frequent Contact	-.03 (.14)
Mean Support Functions	-.08 (.14)
Mean Tie Strength	-.28 (.14)*
Bridging Social Capital	
Network Size	.54 (.11)* **
Effective Size	.37 (.12)* *
Diversity (Adjusted for Network Size)	.00 (.16)
Strength of Weakest Tie	-.47 (.11)* **

* $p < 0.05$; * * $p < 0.01$; * ** $p < 0.001$ (*Two-tailed tests*)Notes: (a) Covariates include gender, age, education, living situation, and baseline depression and anxiety. (b) Social network measures are standardized but precautions are not. (c) Robust standard errors in parentheses.

Table 4
Do Social Networks Predict Mental Health?.

	Loneliness *(Standard Deviations)*	**Perceived Stress** *(Standard Deviations)*	**Depression** *(Average Marginal Effects)*	**Anxiety** *(Average Marginal Effects)*
Bonding Social Capital				
Density	-.20 (.07)* *	-.13 (.07)	-.11 (.07)	-.20 (.10)*
Proportion Kin	-.14 (.08)	-.11 (.09)	-.01 (.08)	-.12 (.09)
Proportion Close	-.15 (.10)	.02 (.08)	-.08 (.08)	.08 (.09)
Proportion Frequent Contact	-.13 (.08)	.06 (.08)	-.01 (.08)	.17 (.08)*
Mean Support Functions	-.00 (.08)	-.00 (.09)	-.18 (.07)*	-.16 (.09)
Mean Tie Strength	-.24 (.09)*	-.04 (.09)	-.19 (.07)* *	-.12 (.08)
Bridging Social Capital				
Network Size	-.04 (.08)	.01 (.08)	.07 (.07)	.12 (.08)
Effective Size	.05 (.09)	-.02 (.08)	.08 (.10)	.15 (.09)
Diversity (Adjusted for Network Size)	.03 (.09)	.17 (.08)*	.12 (.08)	.21 (.10)*
Strength of Weakest Tie	-.23 (.08)* *	.04 (.07)	-.17 (.06)* *	-.16 (.08)*

* $p < 0.05$; * * $p < 0.01$; * ** $p < 0.001$ (*Two-tailed tests*)
Notes: (a) Covariates include gender, age, education, living situation, and baseline depression and anxiety. (b) Social network measures, along with the loneliness and perceived stress scales, are standardized, but depression and anxiety are not. (c) Robust standard errors in parentheses.
Supplementary materials (Tables S1–S8) are available online.

the number of non-overlapping groups in one's network) is associated with 0.37 more precautions ($p < 0.01$). Conversely, network characteristics that predict *fewer* COVID-19 precautions are *density*, *mean tie strength*, and *strength of weakest tie.* A one-SD increase in density (the average closeness between alters in one's network) is associated with a 0.27 drop in precautions taken ($p < .05$); a one-SD increase in mean tie strength is associated with 0.28 fewer precautions ($p < .05$); and a one-SD increase in strength of weakest tie is also associated with 0.47 fewer precautions ($p < .001$).

Crucially, individuals with strong, tight-knit networks—those associated with bonding capital—report taking *fewer* COVID-19 precautions. In contrast, individuals with larger networks—in both absolute and effective size—report taking *more* precautions on average. In terms of magnitude, network size and strength of weakest tie are especially important predictors of COVID-19 precautions.

Mental health outcomes

In Table 4, we examine the relationship between network measures and four mental health outcomes: loneliness, perceived stress, depression, and anxiety.

Loneliness

We use OLS regression to estimate the association between social networks and the loneliness scale. Three measures are significantly associated with loneliness: *density, mean tie strength,* and *strength of weakest tie.* Controlling for covariates, a one-SD increase in density is associated with a 0.20 SD decrease in loneliness ($p < .01$); a one-SD increase in mean tie strength is associated with a 0.24 SD decrease in loneliness ($p < .05$); and a one-SD increase in the strength of the weakest tie is associated with a 0.23 SD decrease in loneliness ($p < .01$).

Perceived stress

We use OLS regression to estimate the association between social networks and perceived stress. Most social network measures were not associated with perceived stress. However, one item—network diversity—is associated with perceived stress: net of covariates, a one-SD increase in diversity is associated with a .17 SD increase in perceived stress ($p < .05$). Recall that our diversity measure is a count of the number of unique relationship types in the network (e.g., friend, coworker) divided by network size. Because diversity is a measure of bridging capital, this finding suggests that increased bridging may be associated with greater stress during the pandemic.

For the next two items, depression and anxiety, the interpretation of our results is somewhat different. Unlike the loneliness and perceived stress scales, for which we lack prior measures, the depression and anxiety measures overlap substantially with the baseline measures. (The difference is that the anxiety items were ordinal at baseline, and the depression measure was more comprehensive, based on the fifteen-item GDS rather than the five-item version). We can therefore interpret the coefficients for depression and anxiety (roughly) as change scores. That is, how do social networks prior to the pandemic predict change in depression and anxiety at the onset of the pandemic?

Depression

As with the COVID-19 precautions checklist, we use binomial regression to estimate the effect of social network characteristics on depression (measured by the GDS-5). Three social network measures are associated with lower depression scores during the pandemic: mean support functions, mean tie strength, and strength of weakest tie. Conditional on covariates, a one-SD increase in the average number of support functions provided by alters is associated with.18 fewer depression items endorsed on the GDS-5 ($p < .05$). Similarly, a one-SD increase in mean tie strength is associated with.19 fewer items endorsed ($p < .01$), while a one-SD increase in the strength of the weakest tie is associated with.17 fewer items ($p < .05$).

Anxiety

We use binomial regression to estimate the effect of network characteristics on anxiety (measured by four items from the Hopkins Symptom Checklist). Four social network measures are associated with anxiety: density, proportion frequent contact, diversity, and strength of weakest tie. Net of covariates, a one-SD increase in network density is associated with.20 fewer symptoms of anxiety ($p < .05$). Curiously, a one-SD increase in the proportion of alters that the respondent sees or talks to often is associated with.17 *more* symptoms of anxiety ($p < .05$). This challenges our argument to some extent, because it suggests that bonding capital can be associated with increased mental health challenges; we will return to this point later on. Finally, a one-SD increase in diversity is associated with.21 more symptoms of anxiety ($p < .05$), while a one-SD increase in the strength of the weakest tie is associated with .16 SD fewer symptoms ($p < .05$).

Of the ten network measures tested here, none were significantly associated with all four mental health outcomes. However, strength of weakest tie was associated with three of the four: loneliness, depression, and anxiety. That is, individuals who lacked a weak tie in their network generally reported better mental health across these three measures. Consistent with the concept of bonding capital, individuals with strong, tight-knit networks generally experienced fewer mental health challenges. Findings were more equivocal for bridging capital, with network size and effective size not significantly associated with any mental health outcome, and network diversity associated only with perceived stress and anxiety. However, the *absence* of bridging capital (as indicated by the lack of a weak tie) was generally associated with better mental health.

Discussion

As psychologists and public health officials have recently suggested, the same conditions that decrease the risk of contracting a virus can also produce loneliness and other mental health challenges (Pietrabissa and Simpson, 2020). While this tradeoff is not inevitable, it is worth taking seriously, and the first step is subjecting the problem to scholarly examination. By leveraging a longitudinal sample of older adults—individuals at high risk of serious complications from the virus—we were able to examine whether network characteristics measured *prior* to the pandemic, along with mental health measures collected during that same period, were associated with various outcomes during the early months of the pandemic (April to June 2020).

We categorized social network measures into two groups: those associated with bridging capital (broad, expansive networks) and bonding capital (dense, tight-knit networks). Overall, measures theoretically linked to bridging capital tended to produce effects in the same direction, while measures linked to bonding capital produced effects in the opposite direction, lending credibility to the operationalization of these concepts.

At the outset of this study, we suggested that the very factors associated with protection from the virus—greater perceived risk and more precautions taken—might be associated with worse mental health. Yet it must be stressed that this is not an inevitable causal relationship: one can take seriously the risk of a pandemic, and engage in protective behaviors, without necessarily sacrificing one's mental health. Rather, our findings suggest that the predictors of risk perception, precautions, and mental health—or to put it more generally, health beliefs, health behaviors, and health outcomes—are each undergirded by distinct social network characteristics linked to the typologies of bridging capital and bonding capital. It is because bridging and bonding are, to an extent, opposite forms of capital deriving from contrasting network structures, that the benefits associated with these forms of capital are sometimes difficult to possess in simultaneity.

Our findings show, for example, that network characteristics associated with precautionary behaviors were indeed linked to worse mental health. In particular, respondents with at least one weak tie (a sign of bridging capital) took more COVID-19 precautions, yet also reported greater loneliness, depression, and anxiety. In contrast, respondents with higher scores on density (a sign of bonding capital) reported fewer health precautions, but also less loneliness and anxiety.

To be clear, the tradeoff between infection prevention and mental health is not absolute. Our results indicate that measures of bonding are associated with mental health advantages and *sometimes*, but not always, physical health risks (i.e., infection); while measures of bridging are associated with physical health advantages (i.e., prevention) and *sometimes*, but not always, mental health risks. Thus, it may be possible to construct networks in an optimal manner to confer both physical and mental health advantages during crises such as the coronavirus.

To caution those who might take this tradeoff too seriously, we note that frequent contact with network members was associated with *heightened* anxiety during the pandemic. While the literature generally suggests that bonding capital is linked to better mental health, this finding implies that it can also increase mental health challenges in the context of a pandemic. Scholars have long noted the "cost of caring" for loved ones experiencing hardship (Kessler and McLeod, 1984), and the COVID-19 pandemic may constitute a unique period in which individuals who frequently check in on their alters face a greater risk of empathetic distress.

Compared to the existing literature, our study has many strengths: First, we leverage longitudinal data from an existing survey on older adults' social networks, mental health, and cognitive outcomes. Second, we simultaneously examine COVID-19 risk perceptions, precautions, and mental health measures—giving a fuller picture of the tradeoffs among them—and we do so during a key period of the pandemic: April to June 2020, just weeks after Indiana's lockdown order began and much of the country's social activity came to a halt (IndyStar, 2020). The Social Networks in Alzheimer Disease (SNAD) project was able to collect data at a crucial moment, when individuals' perceived risk of the pandemic, precautionary behaviors, and mental health concerns were likely at or nearing their peak. Third, we use comprehensive social network data from the PhenX network battery, rather than proxy measures such as those derived from Facebook friends (e.g., Schmälzle et al., 2017) which may not accurately capture the structure of individuals' networks.

However, the study does present some limitations. Because network data are difficult to collect (imposing high respondent burden among other challenges), sample sizes tend to be low relative to other forms of survey data. Models derived from the 113 respondents in this study produced significant associations between network measures and a variety of coronavirus-related outcomes, but readers may be concerned about false positives derived from multiple testing. The results presented here are the work of 60 models: 6 outcomes $\times$ 10 network variables. While multiple comparisons could indeed raise concerns, we feel that the risk of false negatives via adjustment (i.e., p-value correction) outweighs the risk of false positives given the sample size. Additionally, in only one case did the sign (positive or negative) of the significant coefficients reported in Tables 2–4 fall opposite of the expected direction, making it especially unlikely that the pattern of findings presented here occurred by chance.

While our study focuses on an older sample, we make no claims about the generalizability of our findings to younger populations; however, we recognize that our Indiana sample is weighted toward respondents who are white (76% of the sample), female (70%), and highly educated (74% have at least 16 years of education). Future research with a more diverse population may be able to test the generalizability of our findings, though we are currently unaware of a comparable study conducted during the pandemic. Finally, just as social networks influence health outcomes such as depression, so too does mental health influence network composition (Smith and Christakis, 2008; Perry and Pescosolido, 2012). While we controlled for baseline mental health, the extent to which previous mental health challenges have shaped network composition is unknown; future research might use a cross-lagged approach such as the one employed by Li and Zhang (2015) to disentangle such issues of causality.

Conclusion

The effects of COVID-19 on the mental health of aging populations remain relatively understudied. Elucidating the mechanisms through which aging, cognitively impaired populations have responded to COVID-19 should become a priority for future research, as the effects of the pandemic on this demographic have yet to be well understood. Our research suggests that social networks constitute a promising predictor not only of mental health among this population, but also of health beliefs (i.e., risk perceptions) and health behaviors (i.e., precautions) at the height of the pandemic. While the coronavirus has been devastating to the physical and mental health of so many, these findings give us reasons for hope: If social networks measured prior to a pandemic can predict a variety of pandemic-related outcomes, then scholars and policymakers may be able to develop novel interventions that protect mental health while also ensuring that citizens do all they can to prevent themselves and others from contracting the disease.

Declaration of Interest

none.

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IRB approval

This study was approved by the Institutional Review Board (IRB) at Indiana University (Protocol #2006117719).

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.socnet.2022.05.004.

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